Essays on mental characteristics of traders and financial markets

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Part I

Dissertation Overview

Dissertation Overview

Do successful traders and investors have specific individual characteristics or is their success merely luck? Recent research showed that mental characteristics influence economic outcome of individuals. For example individuals with higher analytical reasoning skills earn higher wages, have better education and schooling, are in better employment and occupation situation Cawley et al. (2001), have higher stock market participation Grinblatt et al. (2011) and show a higher degree of consistency in a number of different choice situations (Burks et al., 2009). This cumulative dissertation investigates the influence of mental characteristics of decision makers in financial markets.

As a starting point, I assume that mental characteristics affect what the decision maker perceives as desirable, possible or even thinkable while taking the decision (Hoff and Gauri, 2015). Furthermore, I acknowledge the facts that i) humans have to solve complex decision problems with their limited mental resources and ii) humans behave rationally conditional on their capabilities or "internal constraints" (Simon, 1955), that is they do the best they can. Moreover, I focus on decisions in financial markets, since they are complex tasks: Beside the uncertainty about the future pay-off of the investment, financial markets are also feedback systems for the expectations of others about the future pay-off (Hommes, 2013). This multi-dimensionality (e.g. time, uncertainty about the realization and about others expectation) makes financial markets a good application and testing ground for the influence of mental characteristics on decision making. The mental characteristics investigated are the following:

First, limitations in the information processing (a.k.a. attention): In a period that declares itself as information age ample information and news to process are an omnipresent phenomena. For example a Google search query for the company "General Electrics" generates 920m hits in less than one second, or the Sunday New York Times contains more factual information in one edition than was available to a reader in all the written material of the fifteenth century (Davenport and Beck, 2013). But, humans are limited in their information processing capacities (Kahneman, 1973; Pashler and Sutherland, 1998; Raymond, 2009). Moreover, psychology distinguishes between active information choices and affective, stimulus driven attention. Both are driving factors for the attention of a decision maker and are competing with each other. This rises the the question how do both aspect affect the allocation of the limited attention resources and what are the effects for the financial market?

Second, analytical and mentalizing capacities: An investor on financial markets needs analytical capacities to form an expectation about uncertain outcomes. However, since the price of the asset is also determined by the expectation of others, the investor needs to put himself into the shoes of the other market participants, which we call mentalizing, in order to decode from the price movements the expectations of the others. These are different types of information that are processed separately. The question is, how do the capacities to decode each type of information affects the trading behaviour and thus the market dynamics?

Third, risk-attitude and over-confidence: Since the outcome of an investment on financial markets is uncertain, it seems natural to assume that risk-attitudes have an effect on trading behaviour. From psychological research we also know that decision makers are over-confident in the valuation of their information (i.e. they over-estimate the quality of their own information and underestimate the quality of the others (Odean, 1998)). Given that one cannot process all information and thus makes errors in the expectation formation, over-confidence might affect the trading behaviour and thus the market as a whole.

The aspect of information choice and trading behaviour is discussed in a theoretical framework. The question how analytical and mentalizing capacities affects the investment decision is first reviewed in a conceptual framework to derive predictions. These predictions are tested with an experiment, allowing to test for the individual participant analytical and mentalizing characteristics as well as observe the trading behaviour in an experimental asset market. Beside analytical and mentalizing capacities and among other things, participants were also tested for risk-attitudes and over-confidence, serving as a basis to test for the effects of them.

In the first chapter *Active and Passive Information Acquisition: Application to Financial Markets* I present a model that incorporates the trade-off between active information choice and stimulus driven attention allocation, by assuming that the visibility or salience of information reduces the effort to gather this information. Thus the visibility of an information affects the information choice and at the end the investment decision. The main insights are, first, that a higher visibility of a piece of information increases the informativeness of the asset price and lowers the risk-premium. Second, an increase in the visibility of an asset has two contrary effects on the attention allocation: A higher visibility of asset i makes it relative cheaper to inform oneself about it and this increases the attention on asset i. However, some of the saved resources are spend on informing oneself about other assets, which reduces the attention capacity spend on i. This trade-off leads, ceteris paribus, to a maximum amount of attention an asset can have due to changes in visibility. If the visibility increases beyond that point, the attention allocated to the asset decreases. However, the precision with which the information will be extracted continuously increases in the visibility. Finally, the likelihood of an information to be neglected decreases in the visibility. In addition to the theoretical analysis, I discuss how the distinction between stimulus and goal driven also affects the empirical investigation.[1]

In the second chapter *Cognitive Capacities, Trading Styles and Experimental Asset Market Bubbles* (which is joint work with Andreas Hefti and Frédéric Schneider) we propose that observed heterogeneity in asset market trading behaviour is the result of two distinct, non-convertible cognitive capacities: analytical (“quantitative”) abilities and mentalizing (“perspective-taking”) abilities. We develop a conceptual framework of these two cognitive capacities, which yields testable predictions about individual trading behaviour, revenue distribution and market dynamics: First, individuals will trade most successfully if and only if they have *both* capacities. A person who can mentalize well but has poor analytical capacities will suffer the largest losses. Someone with neither analytical nor mentalizing capacities, will behave erratically and consequently some trading gains will be offset by losses on average. Whereas those traders with only analytical capacities will trade along the fundamental value and thus avoid losses but also miss trading gains. As a consequence, being endowed with just one dimension does not assure trading success, but can be highly detrimental to profits. We test these predictions in a laboratory environment, where we first independently screen subjects’ capacities and then conduct a standard asset market experiment. We had 20 sessions with 2 experimental asset market lasting 15 periods and with 16 participants trading with each other. The expected value in the asset market starts at 360 Rappen and declines by 24 Rappen in each subsequent period. Usually the market price stays above the expected value and crashes towards the end of the experiment. We find individual trading gains and patterns to be strongly consistent with the hypothesis. Moreover, we observe that participants being endowed with both capacities start to sell their assets before the peak of the bubble and initiate the crash of the market price. Finally, markets with on average higher analytical capacities trade closer to the expected value, while markets with on average lower analytical capacities trade on higher prices. There is no effect for the average mentalizing capacity in the market. The results suggest that one dimensional measures for strategic sophisti-

[1] Many empirical approaches to measure attention for a specific stock, use appearance of this company in the news (e.g. by counting the number of newspaper articles the stock is mentioned). While this is a good proxy for the stimulus part of attention it does ignore the goal driven aspect. A good proxy for the active information acquisition are real effort tasks (e.g. number of Google search queries, or tweets).

cation abilities, such as the beauty contest, neglect a large portion of the variation. The conceptual framework and the screening method could be applied to other (economic) decision situations and games in order to explain observed heterogeneous behaviour. The findings are also relevant on firm-level policies to select successful traders or on macro-level analysis to understand sources for the dynamics during asset bubbles.

In the third chapter *Re-examining the effects of risk attitude and over-confidence on trading behaviour within experimental asset markets* I use the date of the 40 experimental asset market to re-examine the role of risk-aversion and relative over-confidence in experimental asset markets. The existing experimental literature examining either risk-aversion or over-confidence relies on small numbers of participants, markets or both; the studies changed the size, the length of the markets or the incentive scheme, leading to even fewer observations per treatment. Risk-aversion was tested by giving participants 20 choices between a certain outcome and a risky lottery (Holt and Laury, 2002) and self-reported questions on their everyday risk-attitude. Relative over-confidence was measured by asking people about their relative performance to other participants in an IQ-Test. There are three general observations for risk-aversion measures: (1) First, for the first period, the only weakly significant effect we found is that participant with less self-reported risk-aversion in financial decision making offer more assets to buy. This is not a strong support for the view that the market price usually starts below the expected value in experimental asset markets. (2) The predictions about the role of risk-aversion of the standard noisy rational expectation framework can be mainly confirmed: (a) The more risk-averse participants are, the less they will trade. (b) However, on the aggregated level, there is no correlation between the trading volume and the average risk-aversion in the market. (c) The less risk-averse participants are in a market, the closer they trade on the declining fundamental value. Most of the effects found over all periods are small, (weakly) significant and mainly driven by the final periods. (3) Finally, comparing the risk-aversion measured by the Holt-Laury lottery task and the self-reported questions, the latter show more often correlation with individual trading behaviour and market outcomes over the whole asset market. On the individual level, the only (weakly) significant effects of relative over-confidence are: Relatively over-confident participants offer more assets to sell after the peak of the bubble. Markets with, on average, higher relative over-confident participants, tend to have a higher trading volume, which is particular large once the bubble burst; these markets trade on higher market prices, in particular, around the peak of the bubble. While the former confirms the theoretical predictions, the latter does not. Both trader characteristics are not pay-off relevant. Together with the weakly significant and small effect size of these trader characteristics, this casts doubt on the explanatory power of these characteristics.

Taking a broader perspective it is not unreasonable to claim, that people fail at decision making from time to time at considerable costs(Ariely, 2015). For more than half a century a large body of research literature documents empirical evidence of deviations from the rational choice model[2] in economics.[3][4] This dissertation adds to this literature by assuming that mental characteristics of the decision makers lead to systematic deviations from the rational choice model. These concepts are applied and tested by decision making in financial market as a complex environment for decision makers. I suggest an approach to model the allocation of limited information processing resources. This model is based on psychological evidence that the allocation of attention is influenced by external stimulus parts as well as by goal driven information acquisition. Furthermore, I investigated together with Andreas Hefti and Frédéric Schneider how the heterogeneity in the ability to process analytical and social information affects trading behaviour, success in the asset market and the market outcome itself. Finally, I carried out a re-examination on how risk-attitudes and over-confidence affects the trading behaviour and asset market outcome. While in the (theoretical) literature both trader characteristics are seen as important, the results of my investigation give only weak support for this view. In sum, this dissertation is only a small part of a broader research agenda for economists.[5]

The structure of the dissertation is as follows: The three papers are found in Part II and the respective appendices are provided in Part III. Part IV contains the bibliography and Part V presents my curriculum vitae.

[2]E.g. Lucas (1972).

[3]Kahneman and Tversky (1979); Simon (1955) and Thaler (1980) are probably the most known pioneers in this field. See Conlisk (1996); Rabin (1998) and DellaVigna (2009) for an overview on this literature.

[4]The rational choice model is a powerful and useful approach, but it ignores human cognition and motivation and thus simplifies the social and cognitive influences on behaviour(Hoff and Gauri, 2015).

[5]The results so far affect also the question of welfare-analysis and thus policy recommendation aiming at maximizing the actual well-being (Chetty, 2015; Hoff and Gauri, 2015). The observed behaviour of the actual humans often generates differences in the experienced utility of the decision maker (i.e. the the actual well-being) and the utility while making the decision (i.e. the objective the decision maker wants to maximize) (Chetty, 2015). Therefore, the deviations from the rational choice model have implications for economic theory to come up with models yielding better predictions about effects of existing policies, as well as the policy tools themselves, by changing default options or framing the incentives (Chetty, 2015). From a pragmatic perspective incorporating behavioural economics into the analysis should be interpreted as a progression of the rational choice model, rather than a defeat(Chetty, 2015).

Part II

Research Papers

1 Active and Passive Information Acquisition: Application to Financial Markets

1.1 Introduction

A large fraction of the workforce in modern economies is occupied with acquiring, processing and synthesizing information as foundations of decision making (Veldkamp, 2011). This paper deals with the acquisition and processing of information as a cognitive process with limited resources driven by the interest in the information provided (goal-driven) and the accessibility or visibility of the information (stimulus-driven). In this manuscript, first I suggest how to model both aspects of information processing and then I apply it to a simple theoretical models of asset markets.

Consider the case of an investor receiving the information needed through his Bloomberg terminal, a provider for financial news and data. Since the space on the screen is limited not all information can be displayed on the screen. Each terminal is personalized to a certain degree for the specific needs of the user. The investor now has to decide which information channel she displays on her screen in a specific size, before she will receive any information at all. It is reasonable that this decision is linked to the set of assets she wants to trade and how uncertain the returns to these assets are in general. A bond with AAA-rating might be less uncertain then a small currency of an emerging economy, making the investor probably to allocate more space on the screen of the Bloomberg terminal to the currency. However, there exists also market wide or global news, which are edited by an editorial board. These global news run through a ticker or special global/market news segment of the screen, highlighting the information displayed there. The decision on this news is thus an external stimulus for the investor, which is not part of her decision which news she wants to track.

The decision situation to the investor personalizing the limited space on the screen of her Bloomberg terminal reflects evidences from psychology which differentiates the usage of the limited attention capacities (Kahneman, 1973; Pashler and Sutherland, 1998; Raymond, 2009) into an active, goal driven and passive, stimulus driven part.[1] The active

[1]To experience both effects, watch the video "Test Your Awareness: Do The Test" produced by Transport of London as a cycling safety advert: http://tinyurl.com/3g3q2jd

attention seems to be common sense, considering oneself behaviour by listening to a certain speaker in a noisy environment the listener turns actively the ear towards the speaker in order to get more information. Beside such introspective deliberations studies show that attention can be focused depending on the task (Shaw and Shaw, 1977). While the active part of attention seems natural, the passive or stimulus driven part is mostly underestimated. However, there is a myriad of evidence that in most everyday decision this part is faster and the most influential (Yantis, 1998). An example of attention scarcity is the number of items under consideration before a purchasing decision varying between two to six items, independent of the grand set of items (Hauser and Wernerfelt, 1990). Mozer and Sitton (1998) report that the respond time in a visual detection task is flat if there are few objects on the screen, but if the number of objects exceeds a certain threshold the respond time increases exponential with the number of visualized objects. While the number of considered alternatives shows little variation the content of this consideration set does and depends mainly on relative visibility, i.e. motion, color or luminance of an object matters relative to the local or also global environment of it (Nothdurft, 2000). The accentuation or spotlight effect enhances the mental processing of the object by the receiver (Maunsell and Treue, 2006).[2] These patterns do also influence decision making on financial markets and influences the aggregate behaviour of markets.[3] These empirical finding can be conceptualized by the distinction of an information poor and information rich environment (Falkinger, 2007). Only if there is a "wealth of information", attention becomes a "scarce resource" (Simon, 1955) and thus has implication for decision making. The exploitation of attention capacities as a scarce resource is influenced by active choice and by visibility, which should be recognized in models dealing with information processing.

[2]With clear behavioural consequences, e.g. the primacy phenomena that has been observed many times on the internet. Web pages that appear higher on the search engine results list have a higher likelihood to be visited (Drèze and Zufryden, 2004). Another example are price listing sites, a company has an increase of 60% of clicks, when the offer is the lowest at such a price listing site (Baye et al., 2009). Or that sales reduces by 83% if a company moves from the first to seventh place in the pricing list (Ellison and Ellison, 2009).

[3]Jacobs and Hillert (2014) report the primacy effect for investment funds with a name at the beginning of the alphabet generating c.p. 0.16% higher money inflows per month, stocks are traded up to 16% more often at more then 10% lower costs compared to the last quarter of firms in an alphabetic order. Beside liquidity, the breadth of ownership, valuation, analyst coverage and local media coverage is larger for a stock earlier in the alphabet. The primacy effect also applies to stock exchanges where the stocks are sorted by a numerical codes, like Japan (Jacobs and Hillert, 2014). Complementing this is the excessive co-movement of stocks in returns, trading volume and volatility with similar ticker symbols (Rashes, 2001), the dotcom effect (Cooper et al., 2001) a stock enjoyed during the dotcom bubble by an abnormal increase in its price after it announced to change the name into internet related dotcom name. Moreover, easy remembered and short names of stocks attract more investors, have a higher turnover and firm value as well as lower transaction price impact due to the higher liquidity (Green and Jame, 2013). One can also look whether information has been ignored in asset pricing.

While rational expectation as standard approach in economic theory assumes that all information is available, this concept might have difficulties to incorporate the insights from psychology on attention and thus to capture the decision problem of an investor as described above; even with rational inattention (Reis, 2006; Sims, 1998) the most widely used deviation in attention economics, one cannot capture all aspects, since these model do assume that all signals come along with the same accessibility or visibility.[4] Other limited attention approaches such as Falkinger (2007, 2008) and Hefti (2011) focus more on modelling the stimulus aspect of attention. For example Falkinger (2007) assumes in a sender-receiver model that each information has to be sent at a certain volume in order to be recognized, if the corresponding volume is to low, the receiver will not take notice of the information.[5] Applying this logic to the above mentioned example one could handle the effects of information being made externally more salient, but could not capture the decision on how to allocate the space on the screen, since it has the drawback that the investor remains passive when it comes to information choice. But especially in the context of asset pricing it is plausible to assume partially active information gathering by the investor.

In this paper I start from the notion that first of all processing information is costly; second, every human has limited cognitive capacities that can be spent on processing information. The utilization of the capacities depends on the one hand on a choice (e.g. which information channel the investor watches on the screen at which size), and on the other hand by factors external to the decision maker (e.g. which information is placed more prominently on the global or market wide information channels). Furthermore I conjecture that a higher salience reduces the required effort to process the information. More specifically, I follow Woodford (2008) who argues that the entropy cost-function (Sims, 1998) is to flexible to explain attention specific outcomes extend the entropy based cost-function with a visibility parameter which reduces the cognitive processing costs.

[4] Rational information choice helps to explain phenomena such under-diversification (Van Nieuwerburgh and Veldkamp, 2009); category-learning of investors (Peng and Xiong, 2006); excess co-movement in asset prices of seemingly unrelated assets and investors home bias (Mondria, 2010); the information choice itself is subject to the underlying decision problem (Hellwig and Veldkamp, 2009), e.g. if one wants to buy an asset the strategies are such that the investor wants to act similar to the other participants, thus the investor wants also to know what the others are knowing. This questions relevance of uniqueness results in the global game literature, once one allows information choice. Caplin and Dean (2013) test rational inattention theories against stochastic choice models within an laboratory experiment. The former does a qualitatively better job of matching this data, since stochastic choice models ignore the link between incentives and attention. Hellwig et al. (2012) study the impact of different information choice technology within a coordination game framework.

[5] His focus is on the "production" of salience in the competition of senders for attention and on the equilibrium diversity of perceived information sources. A more detailed literature overview on stimulus- and goal-driven attention can be found in Hefti and Heinke (2015).

Thus both choice and stimulus influence the information processing process and therefore the decision made.

Compared to standard entropy based cost-function, the main insights are that a higher visibility of a piece of information lead to a higher informativeness of the market price and a lower risk-premium. The likelihood of an information channel not to be followed decreases with accessibility of the information. An increase in the visibility of an asset has two contrary effects on the attention allocation.[6] On the one hand more visibility of asset i eases the information extraction for it, thus it makes it relative cheaper to inform oneself about it and this increases the attention on asset i. On the other hand, one can spend some of the saved resources on informing oneself about other assets, which reduces the attention capacity spend on i. This trade-off leads, ceteris paribus, to an maximum amount of attention an asset can have due to changes in visibility. If the visibility increases beyond the point of the maximum attention, the attention allocated to the asset will decrease. However, the precision with which the information will be extracted continuously increases in the visibility.

In the remaining manuscript, I first introduce the information environment, the learning problem and the modelling of the information processing in section 1.2. Then I continue with the application to a simple asset pricing framework in section 1.3. The manuscript concludes with a discussion on the implications of the results for measuring attention and testing for attention effects as well as real world implications in section 1.4.

1.2 Information Environment and Learning Problem

This section introduces the information environment and discusses the learning problem, which are both essential to the attention allocation decision. Taking an abstract view on an investor, r, the basic decision of her is to choose the amount q of an asset she wants to hold. The asset itself pays out a stochastic dividend $\tilde{d}^*$ with expectation $\mathbb{E}[\tilde{d}^*] = \mu^*$ and variance $var[\tilde{d}^*] = \sigma^*$. Since the investor r does not observe the true dividend process $\tilde{d}^*$ the investment decision q will be based on r's belief $\tilde{d}^r$ of the true process $\tilde{d}^*$. Starting from the premises, that the investor is also a receiver of informative signals about $\tilde{d}^*$, this section takes a closer look on the sender - receiver interaction in order to understand what produces the belief $\tilde{d}^r$.

Sender s distributes an information $\tilde{d}^s$ about the true process $\tilde{d}^*$. The sender s can decide with which *visibility* $v \in \mathbb{R}_+$ the information $\tilde{d}^s$ will be distributed, in the Bloomberg terminal example this is the decision by the Bloomberg editors whether an information

[6] Similar to the income and substitution effects in a households budget allocation.

is placed on the general global, market level or firm specific news-flow. Additionally the sender s sets the *precision* τ_s of the news, which finds its equivalent in the quality or clarity of the information.[7] More technically the *sender-precision* τ_s works as a filter of the noise involved in the reporting process. Thus one can formalize the information the sender s reports about the true process $\tilde{d}^*$, as:

$$\tilde{d}^s = \tilde{d}^* + \frac{\epsilon_s}{\tau_s}, \tag{1.1}$$

with $\epsilon_s \sim N(0,1)$ as an exogenous noise process and uncorrelated with the true process $\tilde{d}^*$. Consequently the variance of the information $var[\tilde{d}^s]$ distributed by the sender s is given by:

$$var[\tilde{d}^s] = \sigma^{*2} + \frac{1}{\tau_s^2} \equiv \sigma_s^2. \tag{1.2}$$

In sum the send s distributes the information on the asset of interest as a package consisting of the tupel $\{\tilde{d}^s, v\}$.

Receiver r observes the tupel $\{\tilde{d}^s, v\}$. The reciever r is a Bayesian agent and holds an unbiased beliefs about the stochastic processes behind the dividend and the information distributed by the sender s. These beliefs equal the true processes (i.e., her a prior beliefs are μ^*, σ^* and τ_s). In terms of the introductory Bloomberg terminal example, this means that she has knowledge about the quality or precision of the average news distributed through the Bloomberg network and the average dividend she can expect from it as well as its volatility. While reading the Bloomberg news she extracts information about the amount of dividend she can expect in the current period by owning the asset. Formally, she receives a noisy signal $\tilde{d}^r$ upon the information $\tilde{d}^s$:

$$\tilde{d}^r = \tilde{d}^s + \frac{\epsilon_r}{\tau_r} \tag{1.3}$$

where $\epsilon_r \sim N(0,1)$ as an exogenous noise process and independent of ϵ_s and $\tilde{d}^*$. The precision of r's information extracting depends on r's attention allocation (see below). The variance of receiver r's signal is given by:

$$var[\tilde{d}^r] = \sigma^{*2} + \frac{1}{\tau_s^2} + \frac{1}{\tau_r^2} \equiv \sigma_r^2. \tag{1.4}$$

The precision τ_r with which receiver r filters the noise depends on r's screen space allocated to the specific news flow. Since more screen space goes along with more detailed

[7]Note that $\tilde{d}^*$ and v are the choices of the sender s. However the remaining analysis focuses on the decision of the receiver, thus for the sake of simplicity $\tilde{d}^*$ and v will be treated as set by the sender without discussing the details of the decision problem of the sender.

information, headline vs. abstract, I assume that the precision τ_r is determined by the effort $\mathbb{I}$ r spends on extracting information from $\tilde{d}^s$. This represents the active, goal-driven choice of attention. The visibility v reduces the required effort $\mathbb{I}$ to extract information from $\tilde{d}^s$ with precision τ_r, representing the stimulus driven attention allocation. Moreover, I assume that the sender precision τ_s decreases the effort to extract information out of sender's information. In sum, the the effort $\mathbb{I}$ represents the *cost-of-producing* τ_r, with the following specification satisfying these assumptions:[8]

$$\mathbb{I}\left(\tau_r, v, \tau_s^2\right) = \frac{1}{2v}\log_2\left(\frac{1}{1-R_{sr}^2}\right) = \frac{1}{2v}\log_2\left(\frac{\sigma_r^2}{\sigma_r^2 - \sigma_s^2}\right) \tag{1.5}$$

with the correlation coefficient $R_{sr} = \frac{Cov(\tilde{d}^s,\tilde{d}^r)}{\sigma_s \sigma_r} = \frac{\sigma_s}{\sqrt{\sigma^{*2}+\frac{1}{\tau_s^2}+\frac{1}{\tau_r^2}}}$. The suggested specification is a slight modified version of the core of used by the rational inattention literature motivated by Sims (1998), by multiplying the mutual information function,$\frac{1}{2}\log_2\left(\frac{1}{1-R_{sr}^2}\right)$, with $1/v$.[9] Note that the effort to extract information becomes infinitely large, $\mathbb{I} \to \infty$, if the sent information becomes barely visible, $v \to 0$, or the receiver r wishes to extract the information with enormously high precision, $\tau_r \to \infty$.[10] On the other side if the information becomes very salient, $v \to \infty$, or the receiver extracts the information with a low precision $\tau_r \to 0$, implying $R_{sr} \to 0$, the effort cost to process this information tends towards zero $\mathbb{I} \to 0$.

The notion of attention as a limited resource is modelled by assuming an upper-bound, κ, on the effort the agent actually can conduct by informing himself:

$$\mathbb{I}\left(\tau_r, v, \tau_s^2\right) \leq \kappa \tag{1.6}$$

One can interpret κ as the overall space available on the screen of the Bloomberg terminal.

1.3 Application to the financial market

This section applies the information processing described above to the underlying investment decision problem[11] Consider a two period economy with one investor acting as a price taker and one risky asset. The investor has an initial endowment $e \in \mathbb{R}_+$ she can either spend on consumption today or buy shares of the asset and use the stochastic dividend $\tilde{d}_{t+1}^*$ per share for consumption in the second period. First, the simplest one

[8] Of course there are other specifications conceivable (e.g. an additive one).

[9] For details see appendix A.1.

[10] Since the correlation $R_{sr} \to 1$.

[11] A version of (Biais et al., 2010).

asset case will be discussed in detail to introduce the environment and look at some basic mechanics of this model. In a second step the multiple asset case will be analysed.

The timing of events is summarized in figure 1.1. The decision making is a two period asset investment problem, with the first period, t, as the investment period and the second period, $t+1$, as realization period. At first the sender s decides on the visibility v and precision τ_s with which she wants to inform about the dividend process $\tilde{d}^*_{t+1}$.[12] Then the investor r decides with how much effort she will extract the information from the signal $\tilde{d}^s_t$, thus she decides about the precision τ_r with which she follows the news-flow on her screen. Subsequently nature N draws the white noise errors $\epsilon_{s,t}$ and $\epsilon_{r,t}$. With the signal about the dividend process $\tilde{d}^r$ at hand the investor chooses the amount of her endowment $e \in \mathbb{R}_+$ she wants either to consume in the current period, c_t, or invest into the asset, yielding the dividend d_{t+1} in the second period financing the consumption c_{t+1}. Thus she decides in period t upon the amount $q_t p_t = e - c_t$ she wants to invest into the asset with q_t as the quantity she wants to hold and p_t as the price of the asset. The price for the asset is such, that the market clears. Note that once the investor received her signal $\tilde{d}^r_t$, the uncertainty arises only in period $t+1$ due to the unknown dividend realization.

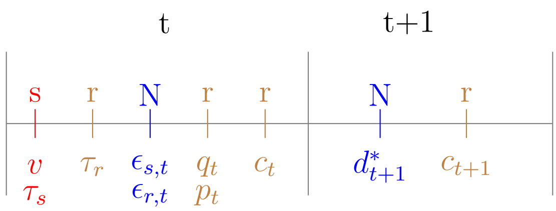

Figure 1.1: Timing of Events

In sum the investor r makes two decisions in the period t, first how precise she wants to extract the information and secondly her investment decision. Since this is a two stage decision problem allows to solve the problem by backward induction. Starting from the last decision to make, the investor solves for the optimal asset allocation given any signal $\tilde{d}^r_t(\tau_r)$, which is informative is but noisy about the dividend realization $\tilde{d}^*_{t+1}$, and the budget constraints for both periods.

$$\begin{aligned}
\arg\max_{q_t} \quad & \mathbb{E}\left[U(c_t) + \beta U(c_{t+1}) \,\middle|\, \tilde{d}^r_t(\tau_r)\right] \\
& \text{s.t.} \\
& c_t = e - q_t p_t \\
& c_{t+1} = q_t \tilde{d}_{t+1}
\end{aligned}$$

[12]Since the focus is on the investors allocation of information processing resources, visibility v and precision τ_s are treated as exogenous.

Following Biais et al. (2010) and I assume mean-variance preferences, $E\left(U_t(c_t)\right) = E(c_t) - \frac{\rho}{2}Var(c_t)$ and $E\left(U_t(c_t)\middle|\tilde{d}_t^r(\tau_r)\right) = E(c_t\middle|\tilde{d}_t^r(\tau_r)) - \frac{\rho}{2}Var(c_t\middle|\tilde{d}_t^r(\tau_r))$ with $\rho \in [0,1]$ as the risk-aversion parameter, allows for a tractable solution to the above described problem.[13] Since there is only one investor in this economy for all shares, with out loss of generality one can normalize the number of shares to one. Together with the market clearing condition one can derive the equilibrium of the investment decision, in which the investor holds all assets, $q_t^{opt} = 1$, at the price given by equation 1.12, which I will discuss later.[14] The optimal solved asset allocation problem can be summarized by the following value function:

$$V(\tilde{d}^r(\tau_r)) = e - p_t + \beta\left(\mathbb{E}\left[\tilde{d}_{t+1}^*\middle|\tilde{d}^r(\tau_r)\right] - \frac{\rho}{2}Var\left(\tilde{d}_{t+1}^*\middle|\tilde{d}^r(\tau_r)\right)\right)$$

Note two things: First, the quantity, q_t, does not appear, since in the equilibrium of the investment decision the investor will hold all assets and thus $q_t^{opt} = 1$. Second, even though there exists an equilibrium price function, the investor takes the price as given and does not consider any effects of her decision on the market price. Therefore she handles p_t exogenous to her decisions.

Using this ease of notation one can turn attention towards solving, the attention decision of the investor choosing the precision with which she wants to extract information. Thus she solves for the optimal attention allocation taking into account the expected valuation given the investment problem will be solved optimally:

$$\max_{\tau_r} \quad V(\tilde{d}^r(\tau_r)) \tag{1.7}$$

$$\text{s.t.}$$

$$\mathbb{I}\left(\tau_r, v, \sigma_s\right) \leq \kappa \tag{1.8}$$

The constraint on information processing effort 1.8 is more interesting in the multi-asset case, however in order to understand the main mechanisms at work I will first continue with the single asset case. The attention allocation can be simplified when one recognizes, that the value function, $V(\tilde{d}^r(\tau_r))$, declines with the variance of $\tilde{d}^r(\tau_r)$ and that the expectation of $\tilde{d}^*$ is invariant with respect to τ_r. Thus the investor wants the variance of the signal $\tilde{d}^r(\tau_r)$ to be as small as possible. Giving some intuition for this: Assume that the investor r made her optimal consumption choice for any signal $\tilde{d}^r$, she maximizes her utility by minimizing the variance in the expected consumption choosing a higher precision τ_r with which she filters the information about the expected dividend. Thus in

[13] See Mondria (2010) p.1842 and Van Nieuwerburgh and Veldkamp (2009) p.782 on a detailed discussion about the implications for the investment decision of mean-variance preferences.

[14] See appendix A.2 for details of the derivation of this equilibrium.

order to solve the attention allocation problem, equation 1.7, it is enough to minimize the uncertainty due to the variance of the signal $\tilde{d}^r$. Thus the attention allocation problem stated in equations 1.7 and 1.8 boils down to

$$\min_{\tau_r} \quad Var[\tilde{d}_t^r(\tau_r)] \tag{1.9}$$

s.t.

$$\mathbb{I}\left(\tau_r, v, \sigma_s\right) \leq \kappa \tag{1.10}$$

According to equation 1.4, the variance of $\tilde{d}_t^r(\tau_r)$ decreases in the precision of the information extraction τ_r and the effort of producing this precision, equation 1.10 also increases with τ_r. Consequently an optimal precision goes along with a binding effort constraint1.10. Thus by construction the optimal attention allocation in the single asset case is a function $\tau_r\left(v, \sigma_s, \kappa\right)$ implicitly defined by

$$\mathbb{I}\left(\tau_r, v, \sigma_s\right) = \kappa. \tag{1.11}$$

It has the following properties: First, $\frac{\partial \tau_r}{\partial \kappa} > 0$, a relaxation of the effort constraint increases the precision of information extraction τ_r, i.e. the more resources are available, the higher will be the precision of the extracted information. In terms of the Bloomberg terminal this means, the larger the screen size of investor r the more space she can allocate to a single news-flow and thus can filter more noise improving the precision of her beliefs. Second, $\frac{\partial \tau_r}{\partial \tau_s} > 0$, if the sent information is less precise, the investor can extract with the same effort only information with a lower precision. Third, $\frac{\partial \tau_r}{\partial \sigma^{*2}} < 0$, if the variance of the dividend of interest σ^{*2} increases, the investor's extract information at a lower precision rate. Fourth, $\frac{\partial \tau_r}{\partial v} > 0$, the higher the salience of the information sent by the sender, the more precise will be the extracted information, which is fairly intuitive as the investor spends less effort in searching the information rather then reading the news and extracting the information she is looking for.

While the first three properties could be easily replicated with a standard rational inattention approach (e.g., Mondria (2010); Van Nieuwerburgh and Veldkamp (2009)); the fourth property is the new aspect of salience of information added to the rational inattention framework.

Turning attention towards the asset price, one has to go back to the equilibrium of the investment decision with the equilibrium asset price:[15]

$$p_t^{eq} = \beta \left[\frac{\frac{1}{\tau_r^2}}{\sigma_s^2 + \frac{1}{\tau_r^2}} \mu + \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}} \left(\tilde{d}_{t+1}^* + \frac{\epsilon_{t+1}^s}{\tau_s} + \frac{\epsilon_t^r}{\tau_r} \right) - \rho \sigma_s^2 \left(1 - R^2\right) \right] \tag{1.12}$$

[15]See appendix A.2 for details how to derive the market price.

An increase in the investor's information extraction precision τ_r has two effects. At first, the re-activity on the signal, $\gamma = \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}}$, becomes stronger the higher the precision τ_r is. The Bayesian rational behind is, that the investor trades-off the prior, the average expected dividend μ, against the newly received information $\tilde{d}_r$; the higher the precision in the information extraction the trustworthy the received information will be and thus the more weight will be put on it by the investor r. Therefore the price itself becomes more informative, which can be seen from the conditional variance about the realization of the dividend $\tilde{d}_{t+1}$ once the price p has been announced, $\Sigma_1 = Var\left(\tilde{d}\middle|p\right)$, decreases in the precision τ_r.[16] Implying that a higher precision goes a long with less uncertainty about the dividend once the price has been observed. Secondly, the risk-premium, $\sigma_s^2\left(1 - \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}}\right)$, decreases in the precision τ_r. A higher precision τ_r in the information extraction implies a reduced uncertainty about the dividend, which makes the investor r demand less compensation for holding a risky asset, leading to a higher price-level, ceteris paribus. The following proposition summarizes the analysis from above.

Proposition 1.1. *A higher information processing constraint κ and/or a higher visibility v of the information, increases the information contained in the market price and reduces the risk-premium, increasing the level of prices.*

Proof. See main text. ■

1.3.1 Multi Asset Case

Before continuing with studying the attention allocation among multiple assets, the (informational) environment and the attention-effort function have to be adjusted for the case of multiple assets. For simplicity, I assume there are I assets with independent and uncorrelated dividend streams. For each asset $i \in I$ the sender sends one piece of information $\tilde{d}_i^s = \tilde{d}_i^* + \frac{\epsilon_i^s}{\tau_i^s}$, where $\epsilon_i^s \sim N(0,1)$ is an exogenous white noise process. Thus similar to the single-asset case one can summarize the variance of the information i by, $var[\tilde{d}_i^s] = \sigma_i^s$. I summarize all information send in the vector $\tilde{\mathbf{d}}^s = [\tilde{d}_1^s, ..., \tilde{d}_I^s]'$ and their variances in the respective vector $\boldsymbol{\sigma}^s = [\sigma_1^s, ..., \sigma_I^s]'$.[17] Since information $i \in I$ is distributed with the visibility v_i, the respective visibility parameters are collected in the vector $\mathbf{v} = [v_1, ..., v_I]'$. The investor r has to decide how precise she will process every incoming information, from this information processing she receives for asset i the noisy signal $\tilde{d}_i^r = \tilde{d}_i^s + \frac{\epsilon_i^r}{\tau_i^r}$ with $\epsilon_i^r \sim N(0,1)$ as an exogenous noise process and τ_i^r as the precision of $r's$ information extracting from the senders information $\tilde{d}_i^s$. Collecting all signals from the investor in

[16] See appendix A.3 for detailed derivation.

[17] The vector of the respective covariances of the signal is zero.

the vector $\tilde{\mathbf{d}}^r = [\tilde{d}_1^r, ..., \tilde{d}_I^r]'$ and the precision with which she extracts the information from the sender by the vector $\boldsymbol{\tau}^r = [\tau_1^r, ..., \tau_I^r]'$. Since the dividend streams of the assets are independent, I assume independence in the effort to extract the information for each asset:

$$\mathbb{I}(\boldsymbol{\tau}^r, \mathbf{v}, \boldsymbol{\tau}^s) = \sum_{i=1}^{I} \underbrace{\mathbb{I}(\tau_i^r, v_i, \tau_i^s)}_{\kappa_i} \tag{1.13}$$

With κ_i being the effort to extract information about asset i and can be interpreted as the attention allocated on asset i and it must hold that $\sum_{i=1}^{I} \kappa_i \leq \kappa$. For analytic tractability I assume the same timing of events and mean-variance preferences as in the single asset case. Thus the asset allocation problem is:

$$\arg\max_{\mathbf{q}_t} \quad c_t + \beta \left(\mathbb{E}\left[c_{t+1} \middle| \tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r) \right] - \frac{\rho}{2} Var\left(c_{t+1} \middle| \tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r) \right) \right) \tag{1.14}$$

s.t.

$$c_t = e - \mathbf{q}_t^{'} \mathbf{p}_t \tag{1.15}$$

$$c_{t+1} = \mathbf{q}_t^{'} \tilde{\mathbf{d}}_{t+1} \tag{1.16}$$

where $\mathbf{q}_t = [q_{1,t}, ..., q_{I,t}]'$ is the vector of quantities hold of each asset and $\mathbf{p}_t = [p_{1,t}, ..., p_{I,t}]'$ is the price vector for each asset. Note that all uncertainty arises in the second period, thus there will be no variance of consumption in t. In equilibrium of the asset allocation the prices are such that all shares of the assets are hold by the investor. The result of the optimal asset allocation can be summarized in the value function

$$V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)) = e - \mathbf{p}_t + \beta \left(\mathbb{E}\left[\tilde{\mathbf{d}}_{t+1} \middle| \tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r) \right] - \frac{\rho}{2} Var\left(\tilde{\mathbf{d}}_{t+1} \middle| \tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r) \right) \right) \tag{1.17}$$

Thus, the attention allocation reads:

$$\max_{\boldsymbol{\tau}_r} \quad V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)) \tag{1.18}$$

s.t.

$$\mathbb{I}(\boldsymbol{\tau}^r, \mathbf{v}, \boldsymbol{\tau}^s) \leq \kappa \tag{1.19}$$

Lemma 1.1. *The attention allocation* $\max_{\boldsymbol{\tau}_r} V(\tilde{\boldsymbol{d}}^r(\boldsymbol{\tau}_r))$ *is equivalent to*

$$min_{\boldsymbol{\tau}_r} Var\left(\tilde{\boldsymbol{d}}_{t+1} \middle| \tilde{\boldsymbol{d}}^r(\boldsymbol{\tau}_r) \right) \tag{1.20}$$

Proof: See Appendix A.4

Applying Lemma 1.1 the solution to the attention allocation problem is then:

$$\frac{\mathbb{I}_{R_i}}{\mathbb{I}_{R_j}} = \frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} \frac{R_i}{R_j}, \tag{1.21}$$

$R_i = \frac{\sigma_{i,s}}{\sqrt{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}}$ is the correlation between the information distributed by sender s on asset i and information extracted by the investor r. In equilibrium the relative marginal effort cost equals the relative correlation of the information the investor extracts from the sender news adjusted by the variance with which the news is sent. In order to get some more details I will now use the specification of the attention effort cost function introduced in equation 1.13, then 1.21 becomes:

$$\left(\frac{1 - R_j^2}{1 - R_i^2}\right)^2 \frac{v_j}{v_i} = \frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} \tag{1.22}$$

Solving this equation for R_j and plugging it back into the attention effort constraint 1.19 one can determine the correlation R_j^{opt} corresponding to the optimal attention allocation. Substituting R_j^{opt} into $\kappa_j = \frac{1}{2v} \log_2 \frac{1}{1-R_j^2}$ we get for the optimal effort allocation:[18]

$$\kappa_i^{opt} = \frac{1}{\ln 4} \frac{1}{1 + \sum_{\substack{j \neq i \\ j=0}}^{I} \frac{v_i}{v_j}} \left(\kappa \ln 4 + \sum_{\substack{j \neq i \\ j=0}}^{I} \left(\frac{1}{v_j} \ln \frac{\sigma_{i,s}}{\sigma_{j,s}} + \frac{1}{2v_j} \ln \frac{v_i}{v_j} \right) \right) \tag{1.23}$$

$$\tau_{i,r}^{2opt} = \frac{1}{\sigma_{i,s}^2} \left(\left[4^{\kappa} \prod_{\substack{j \neq i \\ j=0}}^{I} \left(\frac{\sigma_{i,s}}{\sigma_{j,s}} \sqrt{\frac{v_i}{v_j}} \right)^{\frac{1}{v_j}} \right]^{\frac{1}{\frac{1}{v_i} + \sum_{\substack{j \neq i \\ j=0}}^{I} \frac{1}{v_j}}} - 1 \right) \tag{1.24}$$

Thus in the multi-asset case, the attention allocation does not only depend on the individual characteristics of the asset itself and of the quality of the news with which the information are send about the asset; it is also influenced by the characteristics of all other assets (i.e. the relative properties matter.)

Proposition 1.2. *The optimal attention capacity κ_i^{opt} spend on asset i and the precision with which the information is extracted $\tau_{i,r}^{2opt}$ depends positively on the overall attention capacity κ available and negatively on the variance $\sigma_{j,s}^2$ of the signals of other assets $j \neq i$. While κ_i^{opt} increases with the variance σ_i^{*2} of the underlying dividend stream and decreases in the precision $\tau_{i,s}^2$ of the news distributed by the sender, the effects in $\tau_{i,r}^{2opt}$ are ambiguous.*

Proof. This follows from the derivatives $\frac{\partial \kappa_i^{opt}}{\partial \kappa} > 0$, $\frac{\partial \kappa_i^{opt}}{\partial \sigma_{j,s}} < 0$, $\frac{\partial \tau_{i,r}^{2opt}}{\partial \kappa} > 0$, $\frac{\partial \tau_{i,r}^{2opt}}{\partial \sigma_{j,s}^2} < 0$,

[18] See appendix A.5 for a detailed derivation.

$\frac{\partial \kappa_i^{opt}}{\partial \sigma_i^{*2}} > 0$, $\frac{\partial \kappa_i^{opt}}{\partial \tau_{i,s}^2} < 0$, $\frac{\partial \tau_{i,r}^{2opt}}{\partial \sigma_i^{*2}} \gtrless 0$ and $\frac{\partial \tau_{i,r}^{2opt}}{\partial \tau_{i,s}^2} \gtrless 0$. ■

Consider a change in the variance of the sender's signal $\sigma_{i,s}^2$ about asset i, which might happen due to an change in the variance σ_i^{*2} of the underlying dividend stream of asset i or due a change in the noise (i.e., lower precision $\tau_{i,s}^2$) of the news distributed by the sender. If $\sigma_{i,s}^2$ decreases due to a smaller variance in the dividend stream, the additional gain to learn something valuable for reducing the overall portfolio variance declines. Therefore the investors is less interested in spending more attention resources, lower κ_i^{opt}, on extracting information about asset i. On the other hand, if $\sigma_{i,s}$ declines due to a higher precision in the news distributed, the quality of the news distributed is higher and thus the receiver has to spend less effort herself to extract the desired precision level of information. In both cases the variance $\sigma_{i,s}^2$ decreases and so the attention κ_i^{opt} spent on asset i. If $\sigma_{j,s}^2$ is low[19] there is more overall attention capacity left for asset i and thus κ_i^{opt} as well as $\tau_{i,r}^{2opt}$ increases. These results from proposition 1.2 can also be obtained within a standard rational inattention approach (Van Nieuwerburgh and Veldkamp, 2010). The more interesting effects are with respect to the visibility.

The salience v_i with which the information is sent has two contrary effects on asset $i \neq j$'s optimal attention allocation κ_i^{opt}, as can be seen from the derivative:[20]

$$\frac{\partial \kappa_i^{opt}}{\partial v_i} = \frac{1}{1 + \sum_{\substack{j \neq i \\ j=0}}^{I} \frac{v_i}{v_j}} \left(\frac{1}{2ln4} \frac{1}{v_i} - \kappa_i^{opt} \right) \sum_{\substack{j \neq i \\ j=0}}^{I} \frac{1}{2v_j} \tag{1.25}$$

Recall that κ_i^{opt} is asset i's fraction of the overall attention capacity κ and a change in the visibility v_i reduces the effort to extract the information. If the visibility v_i increases each bit of information becomes relative cheaper and these lower effort costs makes it attractive for the investor r to substitute more of her overall attention capacities towards informing herself about asset i.[21] However, due to a higher visibility v_i the investor can achieve the same precision τ_i^{2opt} with less resources, thus the lower effort needed is distributed partially among all other assets.[22]

Proposition 1.3. *There exists a v_i^* at which the investor's attention for asset i is the highest $\kappa_i^{opt}(v_i^*) = \arg\max_{v_i} \kappa_i^{opt}$, which is decreasing in the overall attention capacity κ and the variance of the news $\sigma_{i,s}^2$ from the sender s about asset i. An increase in the*

[19]Which might happen, due to similar reasons as for $\sigma_{i,s}$.

[20]See appendix A.6 for details of the derivation.

[21]This is similar to the substitution effect when prices change in a consumers expenditure problem.

[22]Similar to the income effect in the consumers expenditure problem.

variance $\sigma_{j,s}$ of the information send about asset j increases v_i^*. However, the precision with which the information is extracted $\tau_{i,r}^{2opt}$ increases continuously in v_i

Proof. See appendix A.5. ■

To grasp some intuition behind, consider the Bloomberg terminal, where the decision maker has only a certain amount of space to display all relevant information for the investment decision in the assets. Thus in general a larger size for the news-flow about asset i, makes the information after reading the news more precise (i.e. increases in $\tau_{i,r}$). However, while a better location, let's say from the stock specific level to the market news-ticker increases the overall reading time for the information on asset i (i.e., increase in κ_i^{opt}) there will be a point, when an increase in the visibility (e.g. from the market to the global news-flow) does no longer increase the reading time. To the contrary, it will decrease κ_i^{opt}, since the information is so easy accessible, that the remaining reading time is better invested in informing about the other assets. This means that there is in optimal visibility, v_i^*, for each piece of information dependent on the underlying parameters (i.e., $v_i^*(\kappa, \sigma_{1,s}^2, ..., \sigma_{I,s}^2, v_j)$). If the investor has less time to read the news, lower κ, the attention maximizing visibility increases and thus a better placement of the article influences the overall reading time spend on this article more than before.[23]
A similar effect on the attention maximizing visibility v_i^* as a decrease in κ has an increase in the variance of signal $\sigma_{i,s}$.[24] Furthermore an increase in the visibility of the piece of information has less impact on the reading time spend for asset i when the variance of the signal becomes larger at the same time [25] and therefore the attention maximizing visibility is reached earlier. An increase in the variance $\sigma_{j,s}$ of the information sent about asset j increases the attention maximizing visibility, v_i^* since there is more to learn about asset j dividend and thus there is a substitution away from attention on asset i towards asset j, leading to less capacities left over for i and therefore having the same effect as a decrease in κ.

The time spend to inform oneself about asset i depends on the overall visibility of the other assets, v_j, in an ambiguous relationship.[26] As discussed in the case of asset i starting from almost invisible pieces of information v_j close to zero, an increase in v_j will lead to a substitution of attention capacities towards asset j, leading to a decrease in the resources left for all other assets. However, after a certain point the information is so visible that the attention spend on it does not increase with a higher visibility, more the

[23]Which follows from $\frac{\partial v_i^*}{\partial \kappa} < 0$.

[24]Which might happen due to either an increase in the variance of the underlying dividend or a decrease in the precision of the newspaper article.

[25]Which can be seen from the cross-derivative $\frac{\partial \kappa_i^{opt}}{\partial v_i \partial \sigma_{i,s}} < 0$

[26] $\frac{\partial v_i^*}{\partial v_j} \geq 0$ iff $\frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} \geq \frac{v_j}{v_i^*}$ and $\frac{\partial v_i^*}{\partial v_j} < 0$ iff $\frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} < \frac{v_j}{v_i^*}$.

contrary happens, since the effort becomes less to extract information about asset j more attention capacities are left over for all other assets, thus the time spend to inform oneself about asset i increases after this point.[27]

Proposition 1.4. *The news-flow about asset i will be neglected, $\kappa_i = 0$, if*

$$4^{\kappa} \leq \prod_{\substack{j \neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}} \sqrt{\frac{v_j}{v_i}} \right)^{\frac{1}{v_j}} .^{28} \tag{1.26}$$

The likelihood, to fall under the threshold 1.26 increases with a lower overall attention resources κ, a larger the number of assets I covered by the investor's portfolio, a smaller variance of the news, $\sigma^2_{i,s}$, about in relation to $\sigma^2_{j,s}$, smaller visibility v_i or the more is to learn about the other assets $\sigma^2_{j,s}$. If $\frac{\sigma^2_{i,s}}{\sigma^2_{j,s}} v_i > v_j$ holds, an increase in the visibility of information on j increases the likelihood of an neglected news-flow of asset i. The opposite holds true for $\frac{\sigma^2_{i,s}}{\sigma^2_{j,s}} v_i < v_j$.

Proof. See Appendix A.8. ∎

An intuition to proposition 1.4 is that some news-flows might be neglected, dependent how large the processing capacities are and how much news-flow the investor has to track. If some assets are less volatile than the other assets and thus the gain is smaller in terms of reducing the conditional variance once the investor spent effort on informing himself, the higher is the likelihood to ignore these assets. This is the result of the goal-direct part of the attention allocation process and one could obtain similar results using the standard rational inattention approach (Van Nieuwerburgh and Veldkamp, 2010). However, if the visibility of the news is still small enough, an increase in the visibility of the news-flow, leads to higher attention-capacity spend on this news-flow. There is also a relative effect, since an increase in the visibility of other assets j up to a certain point (i.e., $\sigma^2_{j,s}$. If $\frac{\sigma^2_{i,s}}{\sigma^2_{j,s}} v_i > v_j$) increases the likelihood for asset i to be neglected. Thus the sender choice of the visibility can influence which news-flow gets neglected or not, reflecting the stimulus driven part of the attention allocation process.[29]

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[27]See Appendix A.7 for the derivatives.

[29]While in this manuscript the sender remains passive, evaluating $\frac{\delta \kappa_i^{opt}}{\delta v_i}$ gives intuition for consequences for sender behaviour discussed e.g. (Falkinger, 2007; Hefti, 2011), with senders competing to draw attention on their news or being neglected. In these models the competition among attention usually works by aiming to achieve a relative salience strong enough to pass a hurdle in the attention perception of the receiver.

1.4 Discussion on measuring attention

Several approaches try to measure attention, one can classify these measures following the distinction of active and passive information choice: Media coverage is an intuitive and practicable proxy for stimulus driven attention, since the fact that a news appears in the media is a decision made by the distributors. Higher media coverage of a share correlate high abnormal trading volumes and extreme one-day returns (Barber and Odean, 2008; Fang and Peress, 2009); stronger momentum effects especially for stocks with high earning uncertainty Hillert et al. (2014). Peress (2008) uses the total number of firms mentioned in the Wall-Street Journal as attention-grabber. Individual investors tend to be net buyers of 'attention grabbing' stocks, measured by media coverage. One issue with media coverage is to differentiate between the impact of the event and the effect of the report about the event, Engelberg and Parsons (2011) circumvent this by looking on articles about earnings announcements in local newspapers and report significant influence of local media on the trading behaviour in these regions.[30] Engelberg et al. (2012) document large overnight returns of stocks after they where recommended in a popular TV show, these spikes reverse over the next few months. Soccer matches compete among attention resources, too, Ehrmann and Jansen (2012) document that the trading volume in a countries stock exchange drops by 55% during a match if the national team is involved.[31]

Another stimulus drive approach is to focus on special events, e.g. Yuan (2015) focuses on the aggregate and household-level effect of "market-wide attention-grabbing events", such as record levels of the Dow Jones or front page articles about the stock market. High market-wide attention events combined with a high level of the stock market lead shareholders to sell their stocks dramatically, reducing market returns by 0.19% on days after the attention-grabbing event. DellaVigna (2009) argue that investors are most distracted on Fridays due to the upcoming weekend, and thus looked at earning announcements on Fridays and found the post-earning announcement drift is more pronounced when there is strong competition for investors attention.

A way to measure goal driven attention is based on measuring the increase in tasks that require real effort: An increase in the google search volume index indicates a rise in stock prices over following two weeks (Da et al., 2011). Or tweeds contain information

[30] Another work around is to look on the impact of old information about firms, Tetlock (2011) finds that stock returns respond to such stale news, even though in a less pronounced way compared to new information.

[31] Moreover, there seems to be a decoupling from the international stock markets, speaking in favour of a different price formation process during a match. Especially for less salient information the attention was low. Small global price movements, where not reflected in the national stock markets and the returns across individual firms showed lower cross-sectional dispersion, indicating that the information processing took place on a market or sector level rather on a firm specific one.

about short-term forex EUR/USD exchange rate (Papaioannou et al., 2013) and perform better in forecasting the stock market compared to traditional sentiment surveys (Bollen et al., 2011). Also blog entries (Gilbert and Karahalios, 2010) and facebook status updates (Karabulut, 2013) contain information about future stock market movements that are not already in the market data. Preis et al. (2013) found that google search queries are also "early warning signs" for an upcoming downward trend, reflecting individual investors concerns.[32] Changes in the view of financial related Wikipedia pages are also an indicator for investors concerns and predict downturns (Moat et al., 2013). Mao et al. (2011) confirm that Google search queries are especially useful with a higher prediction accurate then normal forecasting models in episodes of major changes and high volatility. Aouadi et al. (2013) confirms this finding and observes that search queries are significant determinants of market illiquidity. Analysing professional traders communication via Instant Messengers one observes that traders write more about today and show less concern about tomorrow if the market volatility is high, and vice versa (Saavedra et al., 2011). Textual analysis of social-media platforms helps to predict future stock returns and earning surprises (Chen et al., 2014).

The main issue with all measures is, that while they measure a part of attention, beside the approaches using textual analysis they do not know the direction of the underlying information. Furthermore, the attention allocated on a certain information increases the precision with which this information is extracted and thus the weight with which the information influences the decision but not the direction of the effect. Thus for the empirical analysis one would assume rather a strong interaction effect between attention measures and fundamentals rather then an influence on more or less trading, higher or lower prices. Summarizing, the fact that some one draws attention towards an information should not be informative, unless there is a bias towards more (less) attention if there special type of news like people are more interested in negative events than in positive ones.[33]

1.5 Concluding Remarks

Huberman and Regev (2001) report a case from 1998 of an exorbitant price movement in an the share price of the biotech company ENMD due to a special report in the New York Times, even though this report did not contain new information for investors familiar with

[32]Moreover, one can construct profitable trading strategies upon key-words reflecting the overall state of the economy.

[33]In the context of media coverage of terrorism in Israel, Melnick and Eldor (2010) find evidence that visibility of the news itself is a signal and observe that bad news have a bigger impact on the economy than good news, which they explain with loss aversion; the effect became smaller overtime.

this topic and therefore could not be the main driver, it must have been the visibility of the information in a special report announced on the first page of a big newspaper.[34]

The anecdotal and the empirical evidence underline the importance of accessibility and visibility of news, even in a context where the investors are interested in gathering actively information relevant for their investment decision. This paper starts from the observation that not all information can be processed and that this processing process itself is subject to a goal-driven aspect and an external stimulus-driven part. Thus first the information processing process is modelled, capturing the goal-driven aspect by letting the investor allocate the processing capacities dependent on her goal to minimize the uncertainty. However, the cost of processing the information varies with the visibility of the information itself, which is assumed to be a decision made by the sender of the information.

This information processing is applied to a simple frameworks of asset pricing. The main findings are that a higher visibility and higher processing capacities lead to a lower risk premium and more informativeness of the price. Furthermore, there exists a visibility of the information sent beyond the investor will decrease the attention resources spend on this information, even-though the information received will become more precise with an increase in its visibility. The investor will neglect an information flow if the number of assets in their investment universe increases, if the information flow becomes less visible or if the outcome of the asset is less uncertain.

Further research might look at markets with agents differing in their information processing capacities (e.g., real world examples would be algorithmic based traders and small investors). A higher information processing capacity should result in an informational advantage over agents with less information processing capacities. This informational advantage could be the source of asymmetric information and thus create an adverse selection problem for agents having lower information processing capacities. The reaction to this adverse selection problem might affect the overall market outcome. Another

[34]On Sunday May, 3rd 1998 an special report in the New York Times (NYT) about a breakthrough in cancer therapy research by the biotech company ENMD caused a jump in the share price from 12.063 the Friday close, up to 85.000 at the opening of the stock exchange and the stock exchanged closed with a price at 50 . The price stayed above 30 the subsequent weeks. While one would expect such a market reaction to new information, the fact is that the breakthrough has been reported couple of months ago in November 1997 the nature magazine had it on its front-page, Times wrote about it in its business section, CNN and NBC mentioned the breakthrough as well. Even the NYT itself reported about this in the Appendix. But the market reaction in November 1997 was barely noticeable. The question arises what caused the market movement in May 1998? The information itself was not new to investors familiar with this topic, which finds support in a follow up article of the author of special report, where he underlined, that this report did not contained new information compared to November 1997. The special report in May 1998 was announced on the first page of the NYT and covered several pages, while the announcements in November 1997 where either fare in the back among other news releases or only visible to those who showed already interest in this topic, e.g. article in Nature.

interesting research path to take, is to apply the suggested attention allocation mechanism on further economic decision making (e.g., with informed consumers interested in consumption goods and firms also competing for attention to sell their products).

2 Cognitive Capacities, Trading Styles and Experimental Asset Market Bubbles[1]

Joint with Andreas Hefti and Frédéric Schneider

2.1 Introduction

Which factors determine who looses and who wins in financial markets? Is it merely luck, or do traders need specific individual abilities, and if so, what kind? Recent research suggests that mental abilities correlate with behavioural trading patterns. One strand of this literature focuses on quantitative or analytical abilities as the key determinant of successful asset trading because these skills are necessary to assess the fundamental value of an asset (e.g., Baghestanian et al., 2012; Corgnet et al., 2013; Noussair et al., 2014). Other researchers suggest that good perspective taking skill or mentalizing ability ought to be the key determinant (Bossaerts et al., 2016; Bruguier et al., 2010; De Martino et al., 2013; Suzuki et al., 2016).

In this paper we argue that the performance of traders cannot be explained as result of a one-dimensional skill spectrum. We propose that only an integrated model of *both* analytical and mentalizing abilities can adequately explain why certain traders are successful while others fail, despite the availability of the same information to all traders. Beside analytical thinking, every trader needs an understanding of the "animal spirits" in the market to stay "ahead of the curve"[2] in order to form an expectation about future profitable developments in the market. Or as George Soros pointed out, sometimes market prices "do not merely reflect the so-called fundamentals; they themselves become one of the fundamentals which shape the evolution of prices" (Soros, 2003, p. 7).[3] We propose that the two abilities, analytical thinking and obtaining a well-calibrated perception of

[1]Parts of this chapter are published as Working Paper No. 234 from the Working paper series / Department of Economics at the University of Zurich.

[2]Keynes, who coined the term animal spirits in this context, was himself a successful speculator. He acknowledged that "there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations [...]" (Keynes, 1936, pp. 161-162).

[3]These moments of "irrational exuberance," when prices detach themselves from the fundamental, are "the psychological basis of a speculative bubble," according to Robert Shiller (Shiller, 2015, p. 7).

the other market participants, involves different and independent cognitive resource of individual traders.

To make sense of asset market data, researchers often assume heterogeneous behaviour across traders (Boswijk et al., 2007; Kaizoji et al., 2015). Explaining, beyond the purely descriptive level, the source of this heterogeneity is a central issue of behavioural research in economics and finance.[4] Our working hypothesis is that the way humans think about investment decisions is the product of two fundamentally different cognitive capacities: The analytical capacity (what we call the A-Dimension) captures a person's grasp of the logical and quantitative aspect of a decision problem, which helps individuals predict the *equilibrium* outcome of a game.[5] The mentalizing capacity (M-Dimension)[6] is "the ability to construct a working model of the emotional states of others" (Reniers et al., 2011, p. 85), i.e. to understand other's beliefs and intentions, which helps to predict their actions.[7] Differences in these two capacities lead to variation in the view on the world and thus heterogeneous behaviour. Psychological and neuroscience studies have shown both abilities are stable and largely independent traits (Reniers et al., 2011; Van Overwalle and Baetens, 2009).

We first conceptualize of how both dimensions influence expectation formation and investment decisions. As a consequence of the two-dimensional, non-convertible nature of cognitive capacities we claim the existence of distinct trading styles dependent on the cognitive capacities mix (cognitive types) and a corresponding non-trivial revenue distribution over the cognitive types. We introduce four stylized types based on their cognitive capacity mix (see figure 2.1). "Featureless" (FL-) types have a low level of both analytical and mentalizing capacities. "Technocratic" (TE-) types have high analytical but low mentalizing capacities. They can deduce the equilibrium outcome of a game but are unable to see any pattern in deviations from equilibrium behaviour. "Semiotic" (SE-) types are aware of others' behavioural patterns and are good at deducing intentionality behind these patterns. We call this type semiotic because this type tries to read the "signs" of intentions in observables (such as the past asset prices). Finally, "sophisticated" (SO-)

[4] As Hommes (2011) on p. 21 notes: "An important challenge to a research program in behavioural economics and finance based on bounded rationality is to come up with a plausible and general theory of heterogeneous expectations."

[5] This includes logical reasoning and mathematical calculations such as expected value.

[6] There are a couple of terms, theory of mind, mentalizing, and cognitive empathy, that are often used interchangeably in the literature. The unifying aspect is the ability to put oneself in *"the shoes of the others"* (Frith and Singer, 2008; Reniers et al., 2011; Van Overwalle and Baetens, 2009).

[7] Even tough, the definition of mentalizing is based on a relation among two person, (i.e. to take the perspective of another person) and at financial markets the trader is confronted with decisions by a group of others, recent studies found the activation of areas in the brain usually associated with mentalizing (Bruguier et al., 2010; De Martino et al., 2013; Suzuki et al., 2016). Bossaerts et al. (2016) suggest to interpret these findings in a way that traders perceive the market as an intentional entity.

types are skilled in both dimensions. They know the equilibrium outcome but are aware of the fact that there can be systematic deviations from this outcome, due to others behaviours.

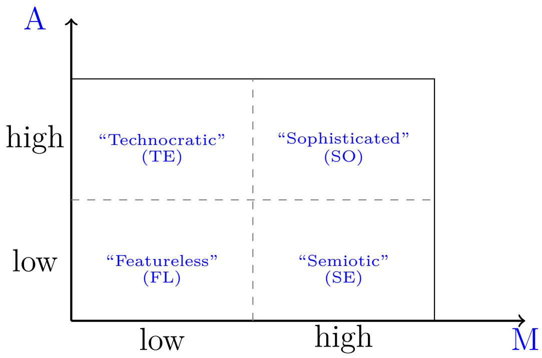


Figure 2.1: The four basic cognitive types
This figure shows the four cognitive types. Due to the independence of the analytical (A)- and mentalizing (M)- capacities, one can plot both cognitive capacities as an ordered pair of perpendicular lines. Each point in this plane represents a specific cognitive capacities mix. In the further analysis we concentrate on four stylized types with four distinct cognitive capacity mixes.

This framework suggests that in the asset market each person forms a mental model of the asset value on the basis of their individual cognitive capacities mix. We posit that each of the two mental dimensions corresponds to one aspect of valuing an asset: To correctly understand the fundamental value of an asset a trader needs analytical ability, and to correctly process the price information of other traders valuations they need mentalizing capacities. This is the basis for a testable model of cognitive capacities and ensuing trading behaviour.

The main predictions of our theory can be summarized as follows. The two-dimensional nature of cognitive capacities generate distinguishable, characteristic trading patterns of the four mental types, which could be described as noise trading (FL-types), fundamental trading (TE-types), trend chasing (SE-types), and bubble riding (SO-types), respectively. The four types vary in their success in the market. In particular, the most successful traders need both mental abilities, because only a combination of these skills allows a trader to appropriately understand both when prices depart from the fundamental and when they fall back. Therefore, we predict that SO will be the most profitable type. Analytical capacity alone does not generate substantial trading gains because a deficit in mentalizing capacity leads to a misinterpretation of price deviations from the fundamental. Therefore, TE will earn less than SO. Conversely, a strong mentalizing capacity alone results in even more serious mistakes: Semiotic traders will detect and follow an upward price trend but miss the optimal exit point since they do not sufficiently account for the fundamental. Accordingly, being skilled in only one dimension is not sufficient to develop a successful trading strategy and may even be detrimental for the final outcome.

In a second step, we conducted a laboratory experiment to test our hypothesis. The laboratory offers the necessary control over the decision environment and the parameters. Most importantly, we can confine trading to a single asset whose expected value we control. Moreover, we can measure individuals' cognitive types independently, record their behaviour in detail, and exogenously manipulate the type composition in markets. The experimental design consisted of two independent phases. In the first phase we ran a battery of incentivized tasks to elicit subjects' cognitive capacities on each dimension. This allows us to categorize the participants into one of the four cognitive types. In the second phase, we observed participants asset trading behaviour in an experimental call-market similar to Smith et al. (1988). This game is a spot market for one asset with known dividend structure; it is a standard paradigm to investigate asset market bubbles. We endow participants with shares of the asset and some cash. In each of the 15 periods of the asset market, they trade shares of the asset among each other. Participants traded by submitting simultaneous bid and ask orders, which allowed us to observe their willingness to pay and accept money for the asset. Participants could not buy shares on credit or sell them short. These asset markets notoriously generate market prices that are above the expected value of the dividend process, this allows us to compare individual behaviour in this bubble environment and individual cognitive capacities.

Our experimental results are consistent with our model predictions. First, as predicted the cognitive capacity mix determines trading behaviour and earnings. Analysing subjects' trading patterns, we see that technocratic types largely trade on the fundamental, buying when the asset price is below or at the fundamental value and selling when the price rises above it; these types make money from the dividend but miss out on the profits from speculating on the bubble. Semiotic types follow the rising asset price, with peak asset holdings slightly after the peak of the bubble; these types lose the most money as they are unable to unload their asset holdings profitably after the bursting of the bubble. The sophisticates anticipate both the rising and the bursting of the bubble and ride it until about two to three periods before its peak; these types make the most money through their superior market timing. Finally, featureless types do not show any pronounced trading pattern and behave erratically. Consequently, some trading gains are offset by losses, which on average leads to small insignificant losses. Summarizing the findings on the subject level, analytical capacities are not enough to maximize trading gains without a strong accompanying mentalizing capacities. Conversely, having *only* mentalizing capacities can be outright detrimental, as these traders will miss the optimal exit point. To become a successful trader, good market timing is indispensable and requires the insight when prices depart from the fundamental and when they revert back. Thus traders, who are strong in both capacities, are most likely to get the market timing right and their success is a joint product of exercising both cognitive capacities.

The different trading patterns help to explain the dynamics in the markets. We observe that the market price is determined by the sell-orders and thus that the sophisticates tend to initiate their sales between the eighth or ninth period, which is before the burst of the bubble. On the aggregate level, the mix of cognitive types should influence the size and length of the bubble. We test these population-based predictions of our model and find that markets with a high proportion of analytically skilled subjects tend to have smaller bubbles.

The results are interesting for institutional traders as they might select traders according to their cognitive capacities to increase trading gains. Furthermore, our results give a better understanding of the dynamics in different markets and thus might help to better target policy intervention on different levels to reduce the size of financial market bubbles. The main implication of our results is that a one dimensional measure, such as the beauty contest, is insufficient to cover the whole variation in the data and neglects important types for the market dynamics. In general as a framework for off-equilibrium behaviour, we believe that our two-dimensional cognitive capacity approach is not confined to financial markets but may be adapted to explain behavioural puzzles in other domains as well. For example, a couple of recent studies examine the role of "strategic sophistication", which we interpret as an combination of our two mental dimensions.[8] It would therefore be interesting to investigate strategic games, such as the Beauty Contest, using our classification of mental types.

In the rest of the paper, we first discuss the related literature in section 3.2. In the subsequent section 2.3 we discuss the conceptual framework in more detail, apply it to the asset market and derive the hypothesis. Then, we explain the experimental design in section 2.4 and present the empirical results in section 3.5. Finally, section 2.6 discusses our findings and concludes this paper.

[8](Bosch-Rosa et al., 2015) find that markets with strategic sophisticates generate smaller than average bubbles. Similarly (Levine et al., 2015) find that strategic sophisticates make higher profits in experimental asset markets. Finally, strategic sophisticates showed higher activation in a brain region associated with Theory of Mind (Coricelli and Nagel, 2009).

2.2 Related literature

A number of contributions considered empirically the consequences of analytical[9] and mentalizing[10] capacities for economic outcomes.[11] The literature so fare did not discussed the interaction effects of the two dimensions of cognitive capacities. Among the large literature on the determinants of traders' behaviour in experimental asset markets we concentrate on those closest to us examining the role of analytical and mentalizing capacities.

Some researchers find an effect of *analytical capacities* both on individual trading behaviour, profits, and bubble size. Participants scoring well in the cognitive reflection test (Frederick, 2005) achieve higher profits in laboratory spot markets (Corgnet et al., 2013) and in spot markets with an added futures market (Noussair et al., 2014); their trading style is less focused on momentum and more on fundamental value (Baghestanian et al., 2012). On the other hand, Bruguier et al. (2010) did not find that cognitive ability is related to the ability to correctly predict asset prices, and Janssen et al. (2015) found no correlation between CRT and behaviour in their speculation task. On the macro level, markets with higher average analytical skills exhibit lower price volatility (Breaban and Noussair, 2015; Cueva and Rustichini, 2015).[12] These observations are in line with studies on actual stock market behaviour. People with higher IQ are more likely to participate in real stock markets, hold a more diversified portfolio, and achieve higher Sharpe ratios than people with lower IQ, even after controlling for socio-demographic covariates (Grinblatt et al., 2011; Korniotis and Kumar, 2010; Luik and Steinhardt, 2015). Among the rare studies that look at *mentalizing capacities*, Bruguier et al. (2010) find that participants who are more skilled in mentalizing are better at predicting rising prices in experimental asset bubbles, which is in line with our own predictions. However, higher mentalizing

[9]Frequently, individual analytical skills are estimated by variations of standard IQ-tests or the Cognitive Reflection Test (CRT, Frederick (2005))

[10]For this dimension there exists no uniform and generally acknowledged measure. However there is a consensus that mentalizing, cognitive empathy or Theory of Mind is a stable personality trait (Reniers et al., 2011) and it consists of sub-traits (Van Overwalle and Baetens, 2009). Some approximations are the Heider-Simmel-Task, e.g. (Heider and Simmel, 1944), the Reading the Mind in the Eyes Test, e.g. (Baron-Cohen et al., 1997) or the QCAE-questionnaire (Reniers et al., 2011).

[11]The main insights are that individuals with stronger analytical skills tend to be more patient, show a higher willingness to take calculated risk, are less loss averse at small-stakes (Benjamin et al., 2013; Dohmen et al., 2010; Frederick, 2005), and make fewer reasoning errors in guessing-games (Rydval et al., 2009). Moreover they bet lower numbers (the Nash prediction) in experimental beauty contest games and are more likely to win (Burnham et al., 2009). For the cognitive mentalizing dimension we know that neuronal networks associated with mentalizing are active when subjects make their decision in games with strategic uncertainty, e.g. the beauty contest (Bossaerts, 2009).

[12]A recent study suggests that bubbles (and high volatility) arise through the interaction between different analytical types (Hanaki et al., 2015).

capacities also correlates with the tendency to ride the bubble too far and to lose money (De Martino et al., 2013).

A couple of recent studies cannot be categorized cleanly along the two cognitive dimensions, analytical and mentalizing capacities, as they use composite measures. Bosch-Rosa et al. (2015) found that markets with subjects, which we would classify as sophisticates generate smaller bubbles than those populated with subjects that we would likely classify as belonging to the other types.[13] Similarly, Levine et al. (2015) found that subjects scoring high on strategic sophistication (as measured by success in Beauty Contest games) make higher profits in experimental asset markets. Crucially, both studies use Beauty Contest Games to measure strategic sophistication, which, in our framework, is equivalent to high analytical and high mentalizing capacities.[14] Because both capacities are necessary to perform well in the beauty contest, these studies cannot easily disentangle the effects of the two dimensions.

According to our conceptual framework, these results tell only part of the story. We contend that the *interaction* of both independent dimensions is relevant for explaining success in the asset market. Thus the gains observed with high analytical capacities are in reality generated by the subgroup of sophisticated types, the same group that is identified through performance in the beauty contest. On the other hand, we posit that most of the losses are made by the subgroup of semiotic types, who have low analytical capacities but *high* mentalizing capacities. Thus our conceptual framework and the empiric results underline a need to examine both dimensions independently.

More broadly, our conceptual framework opens a new avenue to think about behavioural deviations from equilibrium behaviour. Off-equilibrium behaviour, such as asset market bubbles, is outside the scope of traditional game theory. More recent work tries to incorporate behavioural aspects into the existing framework. Some approaches introduce the possibility for random mistakes in people's choices (McKelvey and Palfrey, 1995); others assume that people's responses are optimal, but based on flawed beliefs (Camerer et al., 2004; Stahl and Wilson, 1995). Both approaches can successfully explain a variety of observed deviations from equilibrium but struggle with other behavioural patterns, among others, asset market bubbles.

Our framework is related to both strands of the literature in that we assume that individuals may make mistakes in their best response even if their beliefs are correct

[13]They use a battery of tests consisting of Cognitive Reflection Test (indicative of analytical capacities), "Race to 60" (backward induction, again analytical capacities), and performance in Guessing Games (mentalizing and analytical capacities).

[14]In support of our view, subjects behaving like strategic sophisticates in the Beauty Contest Game showed higher activation in a brain region associated with Theory of Mind (Coricelli and Nagel, 2009), which is equivalent to our mentalizing capacities.

(namely, when they lack analytical capacities), and that they may have mistaken beliefs even if they know how to best-respond (when they lack mentalizing capacities). We add to this literature a specific psychological foundation (differential cognitive capacities), and by testing empirically the predictions implied by that foundation. We think that this approach may be useful for other behavioural regularities beyond the topic of asset market behaviour.

In sum, previous research has theoretically and experimentally used one-dimensional skill-based approaches to heterogeneous non-equilibrium behaviour in games. However, to our knowledge, our paper provides the first theoretical and experimental documentation of two separate and conceptually unrelated cognitive capacities that interact to produce different behavioural types. In our case, we document that two cognitive dimensions interact in a non-trivial way to produce complex trading patterns.

2.3 The conceptual framework

In the asset market all participants know that in this phase they earn what they have as cash holdings at the end of the last period of the game. They can increase these cash holdings by generating trading gains,(i.e. buying cheap and selling high) and by earning dividends. Thus each participant has to evaluate the value of an asset by a (private) forecast of the future asset price based on the observables (i.e., price history and the fundamental value). Understanding the fundamental value component, FV_t, in period t, is a matter of calculating the expected value of the dividend process; it involves the A-dimension. On the other hand, inferring from the price history $P_{t-1} = \{p_0, .., p_{t-1}\}$ the valuation of the asset from the other market participants is more about analyzing the decision situation from the view point of others and to take their perception of the decision situation into account; this needs the M-dimension.[15] Therefore the specific cognitive capacities mix determines each individual's forecast of the market price of the asset.

2.3.1 Expected value of the asset

We assume that the expected value of an asset, $E^i(V_t)$, at time t by individual $i \in \{FL, TE, SE, SO\}$ is a linear combination of its price p_{t-1} observed in the last period and a private signal x_t^i on the asset's fundamental value FV_t.[16]

[15]One might also follow Bossaerts et al. (2016) arguing that traders perceive the market price itself as an intentional entity.

[16]This is in line with standard asset pricing models with informed speculating investors, e.g. Hellwig (1980); Kyle (1989) and Vives (2010).

$$E^i(V_t \mid x_t^i, p_{t-1}) = c_t^i + \alpha_1^i x_t^i + \alpha_2^i p_{t-1}, \tag{2.1}$$

where $x_t^i = FV_t + \sigma_t^i$, with σ_t^i being an white-noise error term and c_t^i is an individual time dependent constant.[17] To account for the role of cognitive capacities in evaluating fundamentals on one side and making inferences from the observed price on the other, we assign to each of the four types shown in figure 2.1 a type specific weighting scheme (α_1^i, α_2^i). More specifically, we hypothesize to reject the following three pairwise null:

Hypothesis 2.1. *Homogeneous trading profiles ($\alpha_1^{TE} = \alpha_1^{SE}$ and $\alpha_2^{TE} = \alpha_2^{SE}$), ($\alpha_1^{TE} = \alpha_1^{SO}$ and $\alpha_2^{TE} = \alpha_2^{SO}$) as well as ($\alpha_1^{SO} = \alpha_1^{SE}$ and $\alpha_2^{SO} = \alpha_2^{SE}$).*

Furthermore, the technocratic-types should mainly respond ceteris paribus to a change of the fundamental, while the semiotic-types will respond ceteris paribus to a change of the last period p_{t-1}. The sophisticated-types should, on average, respond to both components. This implies for the size of weights.

Hypothesis 2.2. *Weighing Size (a) $\alpha_1^{TE} \geq \alpha_1^{SO} > \alpha_1^{SE}$ and $\alpha_2^{SE} \geq \alpha_2^{SO} > \alpha_2^{TE}$*

Being more specific, the size of the weights for the antipodal types, technocrats and semiotic, should differ on *both* the fundamental and the price component.

Hypothesis 2.3. *Weighing Size (b) $\alpha_j^{TE} \neq \alpha_j^{SE}$ for $j = 1, 2$.*

Combining hypothesis H 2.2 and the assumption, that the weights are systematically influenced by the cognitive capacity mix, one can conclude for weights of the featureless type that $\alpha_j^{\mathrm{SO}} \geq \alpha_j^{\mathrm{FL}}$ for $j = 1, 2$. Thus the featureless type has difficulties to decode both components. Thus, we expect featureless types will show more or less unsystematic trading patterns.

2.3.2 Trend of the Fundamental Value, Asset Price Dynamics and Trading Gains

With the expected value,$E^i(V_t)$, at time t per type $i \in \{FL, TE, SE, SO\}$, equation 2.1, we can now conclude the expected market dynamics given a particular trend of the fundamental value, see figure 2.2. For the cases of an constant or increasing fundamental value,

[17]Note that in this analysis risk preferences play no role. In fact, we control for risk preferences in the experiment and find no compelling evidence for a correlation of risk preferences with cognitive types. However, one might think of them as part of the individual constant c_t^i.

we only consider the expected value of each type, while for the case that matches with our experimental set-up, declining fundamental value, we go more into details and derive hypothesis H 2.4 for the expected trading gains of each type. To keep things simple, our analysis starts with the assumption that the price in the last period coincided with the fundamental value of that period.

Constant fundamental value over time: All types will have the same willingness to pay under a constant fundamental value, because the price in the last period was already the same as the fundamental value. Thus independent whether they take the price from the last period (SE), the actual fundamental value (TE), or a mixture (SO), they will form the same expectation about the price of the current period. Even if the market price in the last period and the fundamental value would not coincide, due to the sophisticates and technocratic types, the price will soon converge towards the fundamental value and remain there, with small deviations due to noise trading by the featureless types.[18] The observed trading behaviour of the technocratic, semiotic and sophisticated type should not differ after the convergence. Furthermore, one would not expect a large deviation of the market price from the fundamental value.[19]

Increasing fundamental value: With an increasing fundamental value, the technocrat will increase the willingness to pay and thus their buy offers for the asset per period, while the semiotic type take the lacked asset price into account, underestimating the value of the asset. The semiotic types will behave as a mixture, increasing their expectation of the price for the asset with the increase of the fundamental, but dampen this increase by the lack of the last-period price in the knowledge that they might be able to buy the asset cheaper. In sum, the market price will increase overtime, but stays below the fundamental value.[20]

Decreasing fundamental value: While the technocrats will constantly lower their valuation of the asset, along the fundamental value, the semiotic types stick to the price of the last period and will overestimate the value of the asset in the current period, and sophisticated will mix in her asset valuation between fundamental value and last period price. The resulting market price will be above the fundamental value, only go down

[18] Which might be emphasized by the fact that a constant fundamental value is easy to understand, and thus relatively more people might decode the fundamental value component and behave accordingly.

[19] The size of the bubble is less pronounced in experimental asset markets, with a lump-sum dividend at the end of the market (Caginalp et al., 2001; Noussair et al., 2001; Smith et al., 2000; Stöckl et al., 2015), which can be interpreted as constant Fundamental value overtime.

[20] Stöckl et al. (2015) observe that asset markets with an increasing fundamental value, have the tendency of undervaluation.

slowly and thus there is a tendency of a bubble, even if the asset price was not overvalued before.

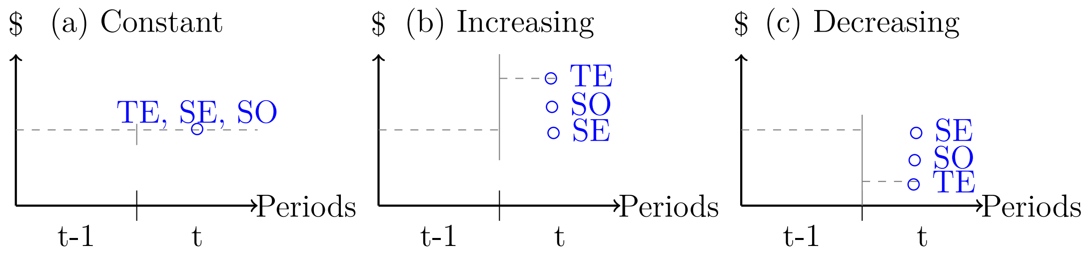


Figure 2.2: Sample Paths of the Fundamental Value and Willingness to Pay
This figure shows sample paths of a fundamental value and for the cognitive types exemplary the willingness to pay in period t given that the price in period $t-1$ was equal to the fundamental value. For simplicity, we assumed that semiotic types always use the price of the last period for their willingness to pay (i.e. $\left(\alpha_1^{SE}=0, \alpha_2^{SE}=1\right)$), technocratic types always use the fundamental value as their willingness to pay (i.e. $\left(\alpha_1^{TE}=1, \alpha_2^{TE}=0\right)$), sophisticated types use a mix of both (i.e. $\alpha_j^{SO} \in (0,1)$ for $j \in \{1,2\}$) and the featureless type is neglected here, due to its unsystematic and possible random trading behaviour. Graph (a) assumes a constant fundamental value, thus each type will have the same price expectation for the actual period. Graph (b) assumes an increasing fundamental value. While the semiotic type will underestimate the value by far, the technocratic type has the highest willingness to pay and the sophisticated will be in between. Graph (c) assumes a falling fundamental value. Here the order is reverse to the previous panel, the semiotic types will have the highest willingness to pay, followed by the sophisticated and technocrats. Even if the price determination is different for the call- and double-auction market, both reflect the average expected values of the market participants over a whole period, and thus in both types of markets we would expect an asset price equal to the fundamental value in (a), an under-valuation in (b) and an over-valuation in (c). Which finds support by laboratory experiments (Stöckl et al., 2015).

As sophisticates will have a higher valuation than the technocratic types, the latter do not hold on to or acquire as many assets as the former. While selling the assets early prevents the technocratic types from incurring heavy trading losses, it also means that they tend to forgo some of the trading gains that sophisticates realize. In sum, we expect technocrats to make non-negative trading gains, but lower gains than sophisticates. A similar comparison between sophisticates and semiotic type, the latter underestimate the fundamental value and thus overvalue the asset relative to sophisticates. The consequences on the trading gains in our experimental asset market are quite severe, because an over-valuation of the asset means that semiotic types buy and hold assets at high prices of which they later cannot get rid at all or only at substantial losses. Thus we expect semiotic types to incur the most substantial losses of all four types. Based on cognitive capacities alone one could superficially conclude that featureless types, should incur the highest trading losses, as they have neither analytical nor mentalizing capacities. However, featureless types fail to account for both the declining fundamental (tending towards holding higher valuations) but also ignore the price component (tending towards lower valuations). While their trading pattern will be more erratic than systematic, some might do profitable trades but at the same time others might incur losses. Thus on average we expect semiotic types to have zero profits from trading or even small losses. We summarize these predictions in the following empirically testable hypothesis:

Hypothesis 2.4. *Trading gains The four cognitive types, $i \in \{FL, TE, SE, SO\}$, earn different trading gains Π_i. Specifically, $\Pi_{SO} > \Pi_{TE} > 0 \geq \Pi_{FL} > \Pi_{SE}$.*

Summarizing the implication of the heterogeneous cognitive capacity mixes on the weights being put on the fundamental value and the last period prices respectively, we conclude: Featureless types will behave erratic [Noise Trading Style]. Technocratic types will trade on the expected value of the asset[21] [Fundamental Trading Style]. Semiotic types will behave follow the trend with sub-optimally late exit timing [Momentum Trading Style]. Sophisticates will ride the bubble and show the best market timing of all types [Bubble-Riding Trading Style].

Sophisticates will therefore also be the most profitable types, semiotic types will suffer the greatest losses, and the two remaining types will show middling performance. Crucially, an improvement in only one capacity does not translate into better performance. Rather, we predict an interaction effect between capacities.

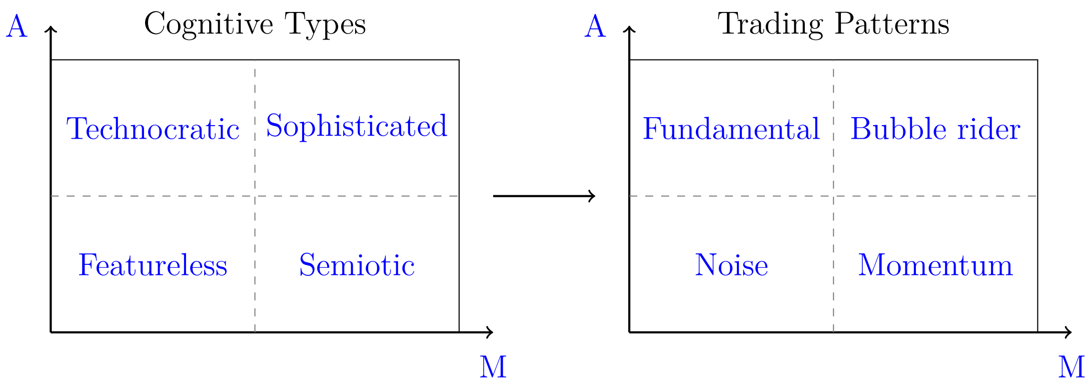


Figure 2.3: From cognitive type to trading patterns

These trading patterns will influence the market dynamics, too. For example, due to the switch of the sophisticated types around the peak of the market price, from buying towards selling the asset, we expect these types be among the first initiating the burst of the bubble. For the macro-level, these dynamics implies that the severity of the bubble depends on the type composition of the market.

[21]This intuition is underlined by a subject note documented in appendix B.1.

2.4 Experimental Design

In order to answer the question whether trading success is merely luck or cognitive capacities, we want control the random factors as much as possible, making the laboratory the natural choice. First, it allows us to measure independently an individual's cognitive capacities through different tasks. Then, we can observe the same individual's behaviour in an experimental asset market giving us maximum control over the market environment. In particular, we can restrict trading to one specific asset with an exogenously set fundamental value, determined through a simple, commonly known dividend process.[22] Importantly, this prevents any form of privileged trading through asymmetric information. We can exogenously endow participants with cash and shares of the asset and choose the market structure, such that participants can simultaneously place buy and sell orders over multiple periods. By recording these orders, we obtain a direct measure of each participant's willingness to pay and willingness to accept. Finally, as discussed in the above section when the asset price experiences a bubble, we expect that each cognitive type will show a distinct trading pattern. Therefore, we use an experimental asset market that reliably produces periods where the asset price is above the fundamental value.

We conducted 20 laboratory sessions, each with 32 participants in the laboratory of the economics department at the University of Zurich.[23] Most of the participants are enrolled at the University of Zurich or ETH Zurich. Each experimental session was divided into two phases. In phase one, each participant passed through a series of tasks that were designed to obtain performance-based measures of the analytical and mentalizing capacities. Each task either involved answering questions or winning a game. For each correct answer or winning a round we rewarded participants with CHF 0.30.[24] In phase two, we grouped the 32 participants into two equal sized groups each constituting one experimental asset market. In the following, the two phases are discussed in more detail.

2.4.1 Phase 1: Measuring Cognitive Capacities

Experimental sessions started by randomly assigning seats to participants, getting them seated in front of their computer terminals and then providing general information about the procedures (see appendix B.3). Subsequently, participants started with Phase one of the experiment. In this phase, they completed a series of tasks. Table B.1 shows the

[22] Quantifying the fundamental value of an asset is usually not possible in real financial markets.

[23] We used hroot (Bock et al., 2014) for recruitment and ztree (Fischbacher, 2007) for programming the experiment.

[24] This form of incentives is standard in experimental economics.

sequence of tasks. The instructions for each task was presented on participants' computer screens, before the task started. Each task was designed to capture a specific aspect of either the analytical or the mentalizing capacity dimension.[25] For each of both capacity dimension we constructed a measure by taking the mean of the percentage of correct answers or won round in the tasks for this capacity. Thus the maximum possible score in one dimension is equivalent to 100, implying that all tasks have been completed without any error.

Table 2.1: Sequence of Experimental Tasks

Phase 1	**Phase 2**	**Exit Questionnaire**
Word Problems Raven's Progressive Matrices Game of Nim *[Risk Attitude Test]* Heider Test Reading the Mind in the Eyes	Experimental Asset Market	Socio-economic survey Financial Literacy Questions

2.4.1.1 Analytical Capacities

For the analytical dimension, we chose three tasks that reflect general intelligence (Raven's Progressive Matrices), mathematical and logical skill (word problems), and strategic reasoning (Game of Nim).

Raven's Progressive Matrices measures non-verbal intelligence. Participants see eight different patterns and, from their arrangement, have to choose the correct ninth pattern from a list of potential answers. We used a version that consisted of 12 items, with a time restriction of 12 minutes for all items.[26] The test measures two underlying abilities of the analytic capacities: deductive ability, requiring to think clearly and make sense of a complex problem, and reproductive ability, requiring to store and reproduce information. The resulting measure for general intelligence is the number of correct answers.

Game of Nim is a simple strategic game for two players (McKinney Jr and Van Huyck, 2006). It consists of a board with several rows, each of which contains a variable number of "stones." Players take turns and successively remove stones from the board. Players can choose any row that still contains stones and can remove as many stones from that

[25]During this phase, we additionally elicited risk attitude, using a standard Holt-Laury price list. The lottery choice was fixed to a 50 : 50 chance of winning either CHF 20 or nothing, and the certain payment moved upward from CHF 0 in increments of CHF 1.

[26]Appendix B.4.1 provides a more detailed description, including instructions.

row as they like. A player wins by removing the last stone from the board. Participants played five consecutive boards with progressively more difficult board constellations. We let participants play this game against a computer opponent that was programmed to best-respond to participants' actions. The participant was always granted the first move, which allowed for winning under the right strategy. There was no time restriction on solving each game.[27] The game is solvable through backward induction, such that success is determined by a player's ability to think strategically.[28] The resulting measure is the number of games won against the computer.

Word Problems consist of seven problems testing for quantitative and logical reasoning from a standard assessment center test for applicants in the finance industry.[29] For each question, subjects had 60 seconds to answer. The resulting measure is the number of correct answers.

2.4.1.2 Mentalizing

Mentalizing is the ability to make accurate inferences about the mental states of others. As stated above, this requires at least two abilities, (1) to recognize and identify others' intentions ("perspective taking") and (2) develop a correct working model about the resulting behaviour ("online simulation") (Reniers et al., 2011). Incentivized tasks assessing both abilities are more difficult to find than for the analytical dimension.[30] We follow Bruguier et al. (2010) and operationalize this ability dimension with two separate tests. In the first one, participant's have to infer other people's mental states (Reading the Mind in the Eyes Test), in the other they have to develop a working model about others intentions from others' actions (Heider-Simmel Test).

The Reading the Mind in the Eyes Test as used by Baron-Cohen et al. (1997) consists of black-and-white photos of human faces expressing a certain mental state (e.g. they look concerned, happy, considered). More specifically, participants can see the eye area of each face and have to deduce the person's intentional state. For each face, participants could choose from a menu of four possible intentional states the picture expresses,

[27] Appendix B.4.3 provides a more detailed description, including instructions.

[28] Nim belongs to the same class of combinatorial games as race games, for example the game "Race to 100" that is used in other studies to measure strategical skill (Bosch-Rosa et al., 2015; Gneezy et al., 2010; Levitt et al., 2011)

[29] The same questions as used in Bruguier et al. (2010). These problems are similar to questions in standardized tests such as the SAT or GRE. The appendix provides a more detailed description (including instructions) B.4.4.

[30] Psychologists mostly use self-reported measures, such as questionnaires (e.g. Reniers et al. (2011)).

without time constraint. The options are such, that under normal circumstances the correct answer is obvious.[31] This test measures the perspective taking abilities by inferring others people mental state. The resulting measure is the number of correct answers.[32]

The Heider-Simmel Task consists of a pair of video clips in which geometric shapes move on a plane imitating intentional social interaction (Heider and Simmel, 1944).[33] The task tests the ability to develop a correct working model about others' intentions and goal-directnesses. Following Bruguier et al. (2010) we used a modified, incentivized version of the original task.[34] We stopped the videos every five seconds and asked the participants to predict whether two of the shapes will be closer together, further apart, or keep the same distance at the end of the next five-seconds sequence. Participants had 5 seconds to answer each question.[35] This version of the task allows a direct and objective assessment whether the given prediction is correct.[36] This test measures the online simulation abilities (, i.e. out of the intentional moves of the geometric figures, the participants should develop a working model allowing them to predict the future moves).

2.4.1.3 Summary statistics of the cognitive capacity measures

The results from the screening phase of all 20 sessions (N=640) shows that the two cognitive capacities are largely independent of each other. Figure 2.4 displays the joint distribution of the two dimensions. The red line shows the linear fit. The corresponding correlation coefficient $\rho = 0.099$ suggests a very weak (but significant) correlation between the two measures ($p = 0.012$, $N = 640$). The black horizontal and vertical lines indicate the median for each dimension (, i.e. 59.37 and 57.3 for the A- and M-Dimension respectively). We use the resulting four quadrants to classify our participants into the four cognitive types, Featureless (FL), Semiotic (SE), Technocratic (TE), and Sophisticated

[31] The appendix provides a more detailed description (including instructions) for Reading the Mind in the Eyes Test B.4.5.

[32] A low score in the Reading the Mind in the Eyes Test is predictive of autism. People with autism disorder score below average on *cognitive* empathy, i.e. mentalizing, but score about the same as healthy controls when tested on *affective* empathy (Dziobek et al., 2008).

[33] The clips are publicly available, for example at `https://www.youtube.com/watch?v=VTNmLt7QX8E`.

[34] The original task asks participants several questions to describe the observed situation and thus relies on free-form verbal responses to assess how much a participant anthropomorphizes the shapes and theorizes about their "intentions."

[35] The appendix provides a more detailed description (including instructions) of the Heider-Simmel-Task B.4.6.

[36] Bruguier et al. (2010) show that a good performance in either test is predictive of the ability to detect whether or not price movements in an experimental asset market are affected by traders with superior insider information and to forecast price changes in such experimental asset market. This underlines that subjects with higher mentalizing capacities detect more easily systematic patterns behind the price process.

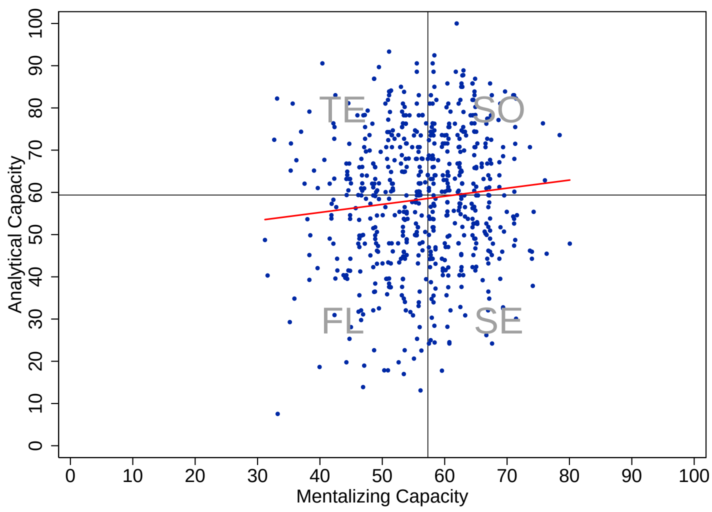


Figure 2.4: Distribution of A and M performance measures
Each dot represents a participant. The horizontal axis shows the participant's performance in the M-Dimension, the vertical axis the performance in the A-Dimension. The dot cloud suggests little relation between the two measures, as highlighted of the red line of best linear fit. The black lines indicate the median for each measure (, i.e. 59.37 (A) and 57.3 (M)).

(SO).[37] Table 2.2 lists the basic summary statistics of the total group and by cognitive type. The participants in each skill category are similar with respect to age, with a mean age around 23 years in all four categories, and we cannot reject the null hypothesis of no contingency ($p = 0.276$, $N = 640$, Pearson χ^2 test). However, the four groups are less balanced with respect to gender (χ^2 test, $p < 0.001$, $N = 640$) because women and men tend to perform differently on the A-Dimension.[38]

We also elicited participants' risk preferences using a Holt-Laury-type choice task (Holt and Laury, 2002).[39] The last column of Table 2.2 shows the average number of times that a participant chose the lottery over the certain amount. The differences across cognitive types are small and we cannot reject the null hypothesis of no contingency (χ^2 test, $p = 0.302$, $N = 640$).[40]

[37]As robustness checks, we conduct our analyses leaving out the participants close to the median and leaving out the most extreme participants, which did no alter the results as reported in the respective appendix.

[38]On average, women score 53.7 points out of 100, and men score about 63.1 points on that scale (t-test, $p < 0.001$, $N = 640$). On the other hand, women tend to perform slightly better on the M-Dimension, where women score on average 57.2 points, and men 55.9 points (t-test, $p = 0.05$, $N = 640$).

[39]A choice among a lottery that yields CHF20 or CHF0 with equal probability or a certain amount. See appendix B.4.7.

[40]Nevertheless, we also demonstrate that all our results remain qualitative similar when controlling for risk attitude.

Table 2.2: Summary Statistics by Cognitive Type

Cognitive Type	Participants	Women (%)	Age (years)	Av. risky choices
Featureless (FL)	171	57.9	23.5	11.7
Semiotic (SE)	159	66.0	23.4	11.0
Technocratic (TE)	150	30.7	22.8	12.1
Sophisticated (SO)	160	43.1	22.9	12.4
Total	640	49.8	23.2	11.8

This table shows some average characteristics for each of the four types. Note that men tend to score higher in the A dimension, resulting in a gender imbalance across skill types.

2.4.2 Phase 2: Experimental Asset Market

For the second phase, we divided participants of each session into two groups with 16 participants each and played a call market version of the Smith et al. (1988) asset market with each of these groups.[41] In each market the 16 participants were endowed with cash and shares of an asset.[42] The asset market lasts for 15 periods. Each period has a trading phase, where participants can trade shares against cash, followed by a dividend phase, where the asset pays a randomly drawn dividend.[43] The random dividend is a standard feature in the experimental asset market, in order to mimic the uncertainty of the fundamental value steaming from the nature of the process. However, even in markets with a certain per-period dividend and thus eliminated risk from the dividend one observes deviations of the market price from the fundamental value (Porter and Smith, 1995). Cash holdings are denoted in Rappen.

In each period, participants can trade shares by submitting one sell order and one buy order.[44] A buy order consists of the maximum price that a participant is willing to pay for a share and the number of shares that the participant is willing to buy if

[41]We implemented a slightly modified version of the call market from the GIMS program for asset market experiments in ztree (Palan, 2015).

[42]A market has 40 assets in circulation and each participant is randomly endowed with one of four possible portfolios: 1 asset and 2228 Rappen; 2 assets and 1956 Rappen; 3 assets and 1684 Rappen; or 4 assets and 1412 Rappen. The amount of cash in each portfolio was chosen such that a participant could earn on average the payment per hour in the laboratory in Zurich (i.e. 2500 Rappen) if he/she would neither buy nor sell through the whole asset market and only earn the dividend. 100 Rappen = 1 Swiss Franc (1 Swiss Franc ≈ USD 0.98 at the time of the experiment).

[43]Shares of the asset have no intrinsic value beyond the dividend stream. The dividend is drawn from the set $d \in \{0, 8, 28, 60\}$, each number with probability 0.25. We generated a random dividend stream at the beginning of the study and used this stream in each of the sessions to keep the inflow of cash constant across all markets.

[44]Appendix B.7 shows the trading screen.

the market price is at most equal to the participant's maximum offer. Conversely, a sell order consists of the minimum price at which a participant is willing to sell a share and the number of shares that the participant is willing to sell if the price is at least equal to the minimum bid.[45] The computer automatically collects all buy and sell orders and calculates a market-clearing equilibrium price.

For our experiment, the call market offers two advantages over a double auction. First, the resulting data are better suited for the analysis of participants' trading strategies, because buy and sell orders can be interpreted as participants' willingness to pay and willingness to accept. Second, the execution of a call market saves time compared to the double auction, which helped us to the duration of the a session manageable.

Aggregate outcome also depends on the market mechanism. Generally, as call markets give fewer opportunities for making offers and trading shares, they exhibit fewer price mirages, are in general closer to the rational expectation equilibrium, and have less trading price volatility than double auctions. The fewer price mirages are mainly the result from the removal of within-period trading dynamics in call markets, reducing the opportunities both for speculative trading (Baghestanian et al., 2014) and for learning about others' trading strategies. Thus, a call market reduces the amount of offers and the size of the asset bubble compared to a double auction, which should limit the downside risk of trend followers and the upside scope for speculation by bubble riders.

2.4.2.1 Market Price and Order Volumes

The average pattern of the market price and order volumes over the 15 periods are shown in figure 2.5. Due to the expected dividend payment of 24 Rappen in each period, in the first period the expected value of the asset is 360 Rappen and it decreases by 24 Rappen in each subsequent period leading to a declining fundamental value (solid grey line). The lowest expected dividend earning from holding an asset is zero over all periods. The highest expected dividend earning from holding an asset is 60 Rappen in each period with a dividend payment. Thus, it starts at 900 Rappen in the first period and it declines by 60 Rappen in each period (dashed grey line). As discussed in section 2.3 given the behaviour of our types, we expect that the market price stays above the downward trending fundamental value.

As in many experimental asset markets, the average market price starts below the expected value of 360 (Palan, 2013), here around 337 Rappen. Subsequently, the price increases until period 6 or 7 - one market already peaked in period 1 (min) another

[45] Participants can leave their buy/sell order blank, in which case they will not buy/sell shares in this period. The computer does not accept orders that violate a participant's budget constraints, that is, buying on credit and short selling are not allowed.

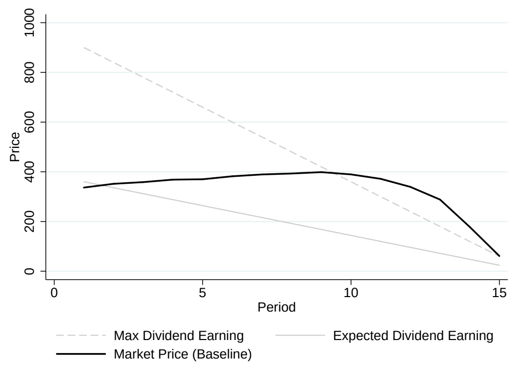


Figure 2.5: Average Market Price (Baseline)
The solid black line shows the evolution of the average market price across all baseline markets. The solid grey line shows the expected value and the dashed line shows the highest possible earnings from the dividends over period 1 to 15.

in period 12 (max). Then, between period 7 and 12 it stagnates or slightly declines.[46] Finally, it crashes towards the end of the asset market. Thus, the deviation of the price from the expected value (i.e. the bubble component) is negative at the beginning and continuously increases afterwards until it bursts, see the grey dashed line in figure 2.8. Due to the stagnating prices during the middle part, the bubble component is largest between period 11 and 12 - where in one market the bubble peaked in period 9 (min) and in another in period 14 (max). In the following, we refer to the period with the largest deviation of the market price from the expected value as the peak period.

Notably the market price tracks closely the sell order prices. The number of assets demanded on the buy side (100 - 200 per period in an average market) exceeds by far the number of assets offered to sell (4-25 per period in an average market). Moreover, while the number of assets demanded by buy-offers stays almost the same over all periods, the number offered assets to sell declines from 25 to 4 towards the middle periods 6-9, till it increases again to 30 towards the end, which leads to a u-shaped pattern in the number of transacted assets itself.

2.4.3 Procedure

All 20 laboratory sessions followed a similar protocol and belonged to one of the following three treatments, affecting the composition of the groups in the second phase. In the baseline treatment (1) we grouped the subjects for the asset market according to their randomly assigned pc number. For the A-seggregation treatment (2) we ranked the subjects according to their performance in the word-problems and grouped them for the asset

[46]In some markets we even observed no trades and thus no prices mainly in this time interval.

market into equal sized high-low groups.[47] In an analogous way, in the M-seggregation (3) treatment, participants were grouped into the asset market by using the Heider-Test performance from phase 1.[48] Before the actual trading in the asset market started[49], we informed the subjects about their own performance and how the other participants in their asset market performed in the respective task.

Table 2.3: Grouping in Treatment Variations

Treatment	**Grouping**	**# Groups/Markets** (High/Low)	**# Participants**
Baseline	Random	16	256
A-Seg.	Word-Problems	12 (6/6)	192 (96/96)
M-Seg.	Heider-Task	12 (6/6)	192 (96/96)

In phase 1, except for the Game of Nim, participants did not receive feedback about their performance.[50] The first phase lasted about 45 minutes, followed by a short break (about 10 minutes) to revive. Phase 2 started with detailed paper instructions, which we read aloud in front of all participants.[51] Participants then had to answer comprehension questions to ensure that the subjects understood the trading rules, especially the declining expected value of the dividends.[52]and the calculation of their final pay-off. The asset market did not start before all participants had answered all questions correctly.[53] Finally, we implemented two pay-off-irrelevant practice periods to make participants more familiar with the computer interface. After the practice rounds, the 15 actual trading periods started. The pay-off for phase 2 was determined by the amount in their cash account at the end of the asset market, (i.e. shares of the asset became worthless after the final period). Phase 2 took on average a little over 90 minutes. After Phase 2 was finished, we administered the exit questionnaire and paid out participants in cash, when they left the laboratory.[54] The earnings for the entire session are the sum of the earnings for the tasks in phase 1, the cash holdings at the end of period 15 in the asset market in phase 2, and

[47]In general, if the there was more than one person having the same value at the cut-off line and we could not split the participants into equal sized groups, we again used the randomly assigned pc numbers to assign those subjects with the same value in either the high- or low-group.

[48]Logistical constraints (especially the short time for preparing the segregation during the session) did not allow for a more precise screening. Appendix B.11.2 reports the type distribution of each asset market, as an ex-post approval that the chosen segregation procedure worked.

[49]After the instructions for phase two.

[50]We summarized performance at the end of the entire experiment.

[51]See appendix B.5

[52]See appendix B.6

[53]Cheung et al. (2014) show that making participants aware of the declining fundamental value in the comprehension questions reduces the bubble size.

[54]The questionnaire is in appendix B.8

a show-up fee of CHF 10.[55] On average, subjects earned around CHF 69.77 with CHF 23.3 being the lowest and CHF 120.5 the highest payments.[56] One entire session lasted about 2.5 hours, which implies an hourly wage of CHF 27.6, excluding the show-up fee.

2.5 Results

This section presents the results from the laboratory experiments and starts with the performance in the experimental asset market in our baseline condition of the four different cognitive types. In a second step we try to analyse how and when the cognitive types generate their gains and losses. In the final step, we look at how the different type distributions affect the market outcome.

2.5.1 Performance

Note that the overall performance in the asset market (, i.e. cash holdings at the end of period 15) is influenced by the trading gains (, i.e. the amount of money earned in addition to dividend payments), and (random) dividend earnings. Since we are interested in the decision taken, we concentrate first on the trading gains as a result of trading shares with other participants.[57] Both trading gains and dividend earnings increase the cash holding at the end of the asset market[58], we used excess return to capture both strategies in a second step. Excess returns are the difference between the actual return from the asset market (i.e., cash in period 15) and a counter-factual passive strategy, that is, the cash a participant would have earned from just holding the initially endowed shares. Consequently this measure shows the added value of the active decision made by the participant, compared to a passive portfolio.

Result 2.1. *The trading gains for all four cognitive types differ as predicted by the conceptual framework, i.e. sophisticates (semiotic) realize the largest trading gains (losses), while featureless and technocratic barely generate notable trading gains. Thus, focusing on just one of the two dimension masks important heterogeneity across cognitive types.*

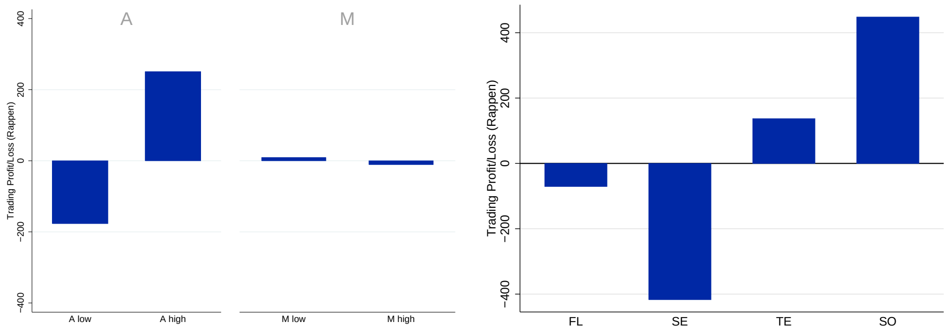
[55] Thus the earnings in phase 1 could not be lost in the asset market, where we endowed each participant with cash and assets, such that if they do not trade, they could earn CHF 25 for the asset market, by holding the original endowment.

[56] Details about the earnings per task are documented in appendix B.2.

[57] Considering the cash holdings at the end of period 15 does not alter the ranking for the overall performance. At the end of period 15 Featureless-types hold on average CHF 28.38, Semiotic CHF 26.86, Technocratic CHF 29.03 and Sophisticated CHF 30.09 in their cash account.

[58] Which was the actual task, since participants received their cash holdings at the end of period 15.

Being better at only one cognitive capacity does not increases trading gains. Moreover, a one-sided specialization on mentalizing capacities leads to substantial losses.



(a) Trading gains across one dimension (b) Trading gains across all four types

Figure 2.6: Trading gains across cognitive types
On the vertical axis, we plot trading income over the entire duration of the asset market for the baseline treatments (N=256). Panel (a) shows both the median split along to the A dimension (left side) and along the M dimension (right side). Viewed in isolation, the A dimension shows a substantial difference in trading gains/losses, while the M dimension does not seem to predict trading success. Panel (b) displays the four different types and uncovers great heterogeneity. The semiotic type incurs most of the losses while the sophisticated type earn most of the profits and the featureless types as well as the technocrats earn zero profits.

The left side of panel 2.6a shows the difference in average trading income between participants who score above the median on the analytical dimension and those who score below the median. In line with most of the existing literature, we find that, on average, better analytical skill translates into trading profits while low analytical capacities results in losses. On the other hand, the mentalizing dimension alone does not explain much (right side of the panel). However, as described in the conceptual framework in section 2.3, we expect that considering the two dimensions in isolation masks substantial heterogeneity. In particular, 94 percent of the profit of the average 250 Rappen profit for those with high analytical capacities accrue to sophisticates, and only 6 percent to the technocratic types. Similarly, of the average 177 Rappen loss for those with low analytical capacities, 99 percent fall to the semiotic type and only 1 percent to the featureless type. Panel 2.6b shows the split into our four cognitive types. Analytical capacities are only a good predictor for trading gains if the participant scores high in the mentalizing dimension, too.

Table B.2 confirms the visual impression from panel 2.6b with a set of OLS regressions of trading gains on three dummy variables : A-high equals one if a participant scored above median on the A dimension, and zero otherwise; likewise, M-high is one if the participant scored above median on the M dimension; and A*M interacts these two variables. We find that the four-type specification (M3) improves upon the two binary type specifications

Table 2.4: Regression analysis trading gains across cognitive types

	m1	m2	m3	m4
A-high	426.828***		34.784	32.859
	(135.771)		(184.485)	(188.558)
M-high		-19.577	-424.671***	-431.895***
		(129.846)	(135.139)	(133.028)
A*M			855.236***	865.240***
			(218.974)	(224.123)
# Lottery				-7.654
				(15.215)
Constant	-176.733***	8.794	-4.034	87.382
	(57.382)	(58.361)	(72.013)	(197.230)
adj.R^2	0.028	-0.004	0.052	0.049
N	256	256	256	256

OLS regressions, standard errors in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Trading gains for entire asset market phase, in Rappen.
Independent variables: Constant: baseline category. "A-high:" dummy for above-median performance in the A dimension; 'M-high:" dummy for above-median performance in the M dimension; "A*M:" interaction between A-high and M-high; # Lottery: number of times a participant chose the lottery over the certain amount in the Holt-Laury task.

(M1 and M2) by uncovering the source of the difference between A-high-types and A-low-types. As seen in the figure, we can show that the bulk of the profits are generated by the sophisticates, who score high on both dimensions, and that most of the losses go to the semiotic types. We find that the semiotic type performs worse than any other type ($p = 0.04$ against FL, t-test, $p < 0.0001$ against SO, $p = 0.05$ against TE, both Wald tests), and the sophisticated type performs significantly better than all other types ($p = 0.004$ against FL, $p = 0.05$ against TE, both Wald tests). However, we cannot reject the hypothesis that the technocratic type does better than the featureless type ($p = 0.87$, t-test).[59] Thus, we find that being good in only one dimension and lacking capacities in the other is at best not different than scoring low on both (in the case of the technocratic type) and at worst disastrous to trading gains (in the case of the semiotic type).

[59]The same is true if we control for risk attitudes in the form of number of risky choices in the Holt-Laury task (M4). If anything, the differences in parameter estimates become larger than in M3. Semiotic type performs worst ($p = 0.006$ against FL, t-test, $p < 0.0001$ against SO, $p = 0.0233$ against TE, both Wald tests); SO performs best ($p = 0.004$ against FL, $p = 0.04$ against TE, both Wald tests). Risk attitude itself has a negligible and insignificant effect on trading gains ($p = 0.0.6$, t-test).

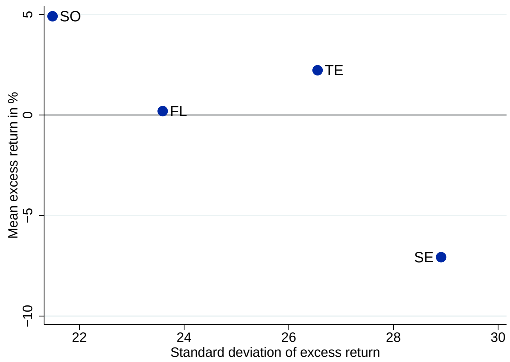


Figure 2.7: Portfolio excess returns

Excess returns compared to passive strategy by cognitive type. Vertical axis shows average excess return, horizontal axis shows standard deviation of excess return across participants within cognitive type. The more to the upper left, the better the performance and the more homogeneous is the behaviour among individuals of the same type. The figure shows that the average sophisticate strategy entails both the highest return and highest consistency in behaviour while the semiotic type has simultaneously the lowest return and the highest heterogeneity among individuals in this group.

While trading gains reflect the performance due to action by the participant, it neglects the potential strategy decision of holding assets and earning the dividend. Therefore we use excess return to capture both strategies. Figure 2.7 shows participants' excess returns across the four cognitive types. We plot the average excess return, separated by cognitive type, on the vertical axis. On the horizontal axis, we plot the standard deviation of excess return across participants within the group of cognitive types. That is, the higher the dot, the better the average excess return of this cognitive type compared to a passive strategy; the more to the left, the more consistent is the type as a group in achieving this return.

We find that the sophisticated types are not only the one with the highest performance but also with the least variation in performance. On the other hand, the semiotic types have both a negative return (meaning this type would have done better leaving the initial portfolio alone) but also the highest variation in performance. The technocratic types have the second highest excess return but show also the second largest variation. Finally, the featureless types have an excess return close to zero and a relatively low variation. Due to the high variation of the returns for most of the types, we run analogously to table B.2 regressions on the total trading income using different quantiles for classifying the types. The main direction of the effects do not change as the results reported in appendix B.10 suggest.

2.5.2 Trading Styles

Following the conceptual framework, the differences in performance of the cognitive types should be the result of different ways of expectation formation and thus heterogeneous trading patterns. The experimental evidence mainly confirms hypotheses (H1-H3) of your conceptual framework.

Result 2.2. *The cognitive types show mainly distinct trading patterns H 2.1 particular in terms of as asset holdings. While the technocrats and semiotic types have opposed trading strategies H 2.3, the sophisticated type shows a mixture of both H 2.2. The sophisticated types are significantly better at solving the timing problem, when to exit the bubble, which enables them to earn higher trading gains.*

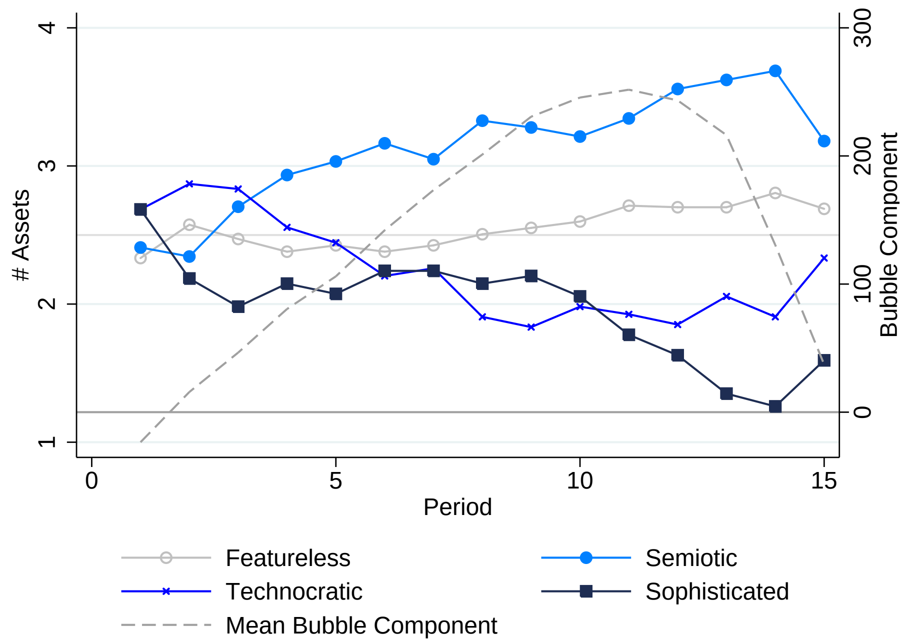


Figure 2.8: Type-wise Mean Asset holding

Mean asset holdings per type over time (left y-axis) and mean bubble component (right axis) (, i.e. the mean of the difference between market price and fundamental value). Note that the bubble component is on average negative at the beginning and increases till period 11 or 12, followed by a sharp decline (, which is a bit later then the market price that on average has its peak in period 6 or 7, followed by a stagnation and a crash from period 12 onwards).

Asset holdings: Successful trades lead to changes in the asset holding and the size of the change depends on the quantity successfully offered. Figure 2.8 plots on the left y-axis the mean asset holdings per type at the end of each period, after all trades are settled and on the right y-axis the size of the bubble[60] as a measure of the average market dynamics.

[60] The mean of the market price less the fundamental value

On average, the semiotic types accumulates assets over time, while technocratic types increase their asset holdings in the first three periods but then quickly sell their assets, apart from an repurchase endgame effect. Moreover, sophisticates sell their assets in the first three periods and then start to increase the number of assets again up to period 6, while holding them and starting a consequent lowering of their asset holdings before the peak of the bubble. Finally, the featureless types holds an almost unchanged stock of assets over all periods.

A variance analysis suggests that there are differences among the four types in terms of asset holdings. Comparing the asset holdings of two types with each other, one can reject the null that the asset holdings are the same at the level of $p < 0.0001$ for the comparison between the LS vs. SE, LS vs. SO, SE vs. TE, SE vs. SO can and at $p = 0.1$ for LS vs. TE. The reaming comparison of the SO vs. TE is insignificant.[61] Table 2.5 regresses for each mental type the asset holdings at the end of each period on the fundamental of the current period and the price of the actual period. Starting with the featureless type in the first column, beside the constant of around 2.8 assets there is no significant effect of either component on the asset holdings. Confirming the visual impression of figure 2.8 that on average the featureless type remain with their asset holdings. In contrast the asset holding of the semiotic type correlates highly significantly negative with the fundamental value and positive with price of the last period. While according to the conceptual framework we would have expected no significant correlation with the fundamental value; the significant positive correlation with the price of the last period is in line with the framework. The technocratic types positively correlate with the current fundamental value, which is also in line with the predictions. , which is in line with the predictions, too. While the positive signs for both components for the asset holding of the sophisticated are in line with the predictions, there is no significance on either component.

Table 2.6 takes on closer look on the differences in the determinants of asset holdings among types. Here the data on asset holdings of two types are pooled[62] together, and additionally we introduced a dummy $i \in \{FL, SE, TE, SO\}$ for one of types and multiplied it with the components. This way we can disentangle the additional effect of belonging to group i in comparison to the other and whether this difference is significant. Starting with the comparison of FL vs. SE in the first column, the regression suggests that belonging to semiotic type makes those participant react significantly more negative on the

[61]Running an F-Test on testing the null that both compared types are the same, yields similar results, with SE vs. SO and SE vs. TE being highly significant different (p-Value<0.001); FL vs. SE and FL vs. SO being significantly different (p-Value=0.05); FL vs. TE and TE vs. SO not being different at all.

[62]E.g.: For the FL vs. SE, for the regression we pooled the data from the participants being either FL or SE and ignored the others

Table 2.5: Determinants of asset holdings per type

	FL	SE	TE	SO
FV_t	-0.001	-0.004***	0.004**	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
p_{t-1}	-0.000	0.003***	-0.004	0.001
	(0.001)	(0.001)	(0.003)	(0.002)
Constant	2.827***	2.944***	2.796***	1.137
	(0.305)	(0.320)	(0.997)	(0.828)
R^2-overall	0.0012	0.0162	0.0093	0.089
N	1176	822	713	729

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Asset holdings at the end of each period
Independent variables: "FV_t:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16 - t) * 24$; "p_{t-1}:" Price in the last period.

fundamental and weakly significant positive to the last period price, than those belonging to the featureless types. The FL vs. TE comparison in the second column suggests only a difference in coefficient for the fundamental, with the TE reacting stronger to it. While the coefficient on both components are similar for the FL vs. SO comparison, there is an overall difference that on average over all periods sophisticated hold 1.7 assets less than the featureless type. The semiotic and technocratic types, those having the diametral cognitive capacities, also differ significantly in their reaction to the fundamental and last period price, with the technocrats following stronger the fundamental value and less the last period price. Comparing semiotic and sophisticated, they differ in terms that the sophisticated reacts more positive to the fundamental value of the asset. The TE vs. SO comparison shows no significant differences in both types' reactions. However, the differences in the coefficients points in the right direction.

Summarizing, the regressions on the asset holding dynamics and willingness to pay and accept mainly support that there are differences among the cognitive types, beside for the comparison among technocratic and sophisticated types.

Table 2.6: Comparison of types - Asset holdings

	FL vs. i=SE	FL vs. i=TE	FL vs. i=SO	SE vs. i=TE	SE vs. i=SO	TE vs. i=SO
FV_t	-0.0008	-0.0008	-0.0008	-0.004***	-0.004***	0.004**
	(0.0008)	(0.0008)	(0.0008)	(0.001)	(0.001)	(0.002
p_{t-1}	-0.0004	-0.0004	-0.0004	0.003***	0.003***	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
d_i*FV_t	-0.003**	0.004**	0.003	0.008***	0.006**	-0.001
	(0.0014)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
d_i*p_{t-1}	0.003*	-0.003	0.002	-0.006**	-0.002	0.005
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)
d_i	0.116	-0.027	-1.691**	-0.147	-1.807*	-1.66
	(0.427)	(1.19)	(0.846)	(1.11)	(0.938)	(1.74)
Constant	2.827***	2.827***	2.827***	2.94***	2.94***	2.8***
	(0.305)	(0.305)	(0.305)	(0.32)	((0.32)	(0.996)
R^2-overall	0.0216	0.0073	0.016	0.042	0.0646	0.0117
Observations	1998	1889	1905	1535	1551	1442

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participants. Data from both groups under consideration is pooled for the specific regression.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Asset holdings at the end of each period
Independent variables: "FV:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16-t)*24$; "p_{t-1}:" Price in the last period. "d_i:" Dummy for i-type; $d_i = 1$ if participant is of type i, zero otherwise..

Timing The question remains what leads to the significant differences in trading gains between the technocratic and the sophisticated, if they respond similar to changes in the fundamental and prices in their expected value[63] as well as in the quantity of assets hold. Figure 2.8 already indicates that the sophisticated on average reduce their asset holdings slightly before the market price reaches it high. Figure 2.9 plots the average net quantity traded per cognitive type (i.e. numbers of assets bought less number of assets sold) around the peak of the market price in period 7 or 8. In general the traded number of assets declines toward the peak of the market price and increases towards the end (when the bubble bursts). The sophisticated types are the only one that are consistently on the net sell-side once the price started to fall (Period 8 onwards), indicating that on the one hand they are better with the timing on average and on the other also drive down the market price with their collective action.

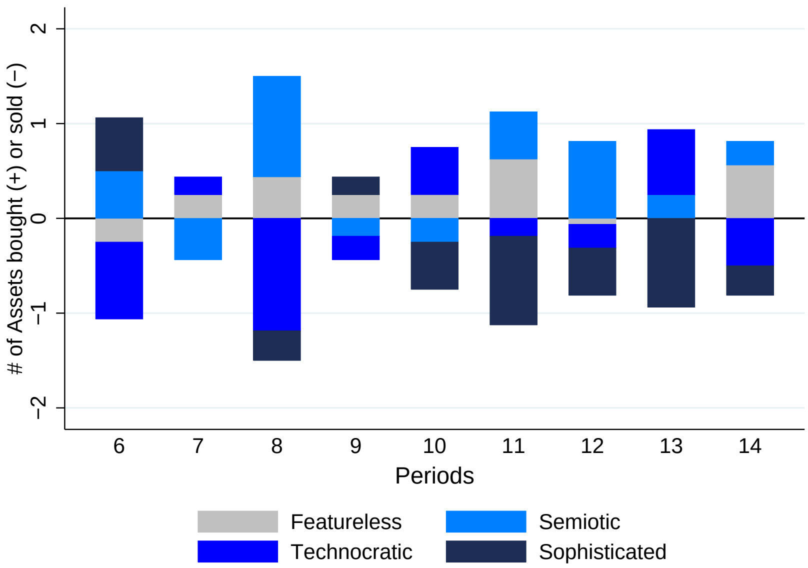


Figure 2.9: Net of successful trades per cognitive type group

This figure shows the net number of successful trades made per cognitive type group over time in an average market, for the periods around the burst of the bubble (, i.e. 6-14). The net number of successful trades is the the sum of all assets bought less the sum of all sold assets per cognitive type group for each period. A positive number means, that this group in total bought more assets in the specific period; a negative number means that the cognitive type group sold more assets as a whole group.

Testing this timing ability, we compared whether the types anticipate an increase or drop in the price for the next period by adjusting their asset holdings. A drop (increase) in the market price of the subsequent period is defined as a market price, p_{t+1}, below (above) the market price of the current one, p_t. Note that, when the subjects make their offers

[63] Approximated by their willingness to accept and pay.

neither p_t nor p_{t+1} have been realized. On average each market experienced $5-6$ periods where the market price went up in the subsequent period, with a minimum of 2 and a maximum of 8 periods; $6-7$ periods where the market price went down, with a minimum of 2 and a maximum of 11 periods. Since the behaviour might be different if a price drops or increases in the next period, we separated the cases and run type wise comparisons regarding the number of assets bought or sold in the current period. Table 2.7 compares the asset change, assets hold at the end of the period less the asset hold at the beginning, in the current period if the price goes up in the next period. This is done by regressing the asset change on dummies for belonging to one of the groups. Take column four, which compares the semiotic and the technocratic types: The constant says that on average the semiotic types buy 0.1 assets if the market price goes up in the next period, which is weakly significantly different from zero. While the technocrats significantly buy 0.26 assets less then semiotics. However, the insignificant constant in column six shows that on average the amount of assets sold by the technocrats does not significantly differ from zero. The bottom line is that only the semiotics buy weakly significant into the asset, if the market price goes up the subsequent period and only technocrats differ significantly in this regard from the semiotics.

Table 2.7: Asset changes if the price goes up in the subsequent period

	FL vs. SE	FL vs. TE	FL vs.SO	SE vs. TE	SE vs. SO	TE vs. SO	SO
SE	0.023						
	(0.098)						
TE		-0.241		-0.264*			
		(0.141)		(0.124)			
SO			-0.160		-0.184	0.080	
			(0.121)		(0.106)	(0.159)	
Constant	0.078	0.078	0.078	0.101*	0.101*	-0.162	-0.082
	(0.062)	(0.062)	(0.062)	(0.055)	(0.055)	(0.104)	(0.083)
adj. R^2	0.000	0.005	0.003	0.006	0.004	0.001	0.000
N	693	637	664	536	563	507	267

OLS estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: Participant. Only those periods where the price went down in the subsequent period.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Asset holdings at the end of period less asset holdings at the beginning of the period.
Independent variables: "d_i:" dummy for $i-$type with $i \in \{SE, TE, SO\}$; $d_i = 1$ if par participant is of type i, zero otherwise.

Table 2.8: Asset changes if the price goes down in the subsequent period

	FL vs. SE	FL vs. TE	FL vs.SO	SE vs. TE	SE vs. SO	TE vs. SO	SO
SE	0.067						
	(0.058)						
TE		0.056		-0.011			
		(0.096)		(0.091)			
SO			-0.173		-0.240**	-0.229*	
			(0.101)		(0.090)	(0.124)	
Constant	0.008	0.008	0.008	0.075*	0.075*	0.063	-0.166**
	(0.042)	(0.042)	(0.042)	(0.036)	(0.036)	(0.073)	(0.074)
adj. R^2	0.001	0.000	0.005	0.000	0.009	0.009	0.000
N	907	848	847	689	688	629	314

OLS estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: Participant. Only those periods where the price went down in the subsequent period.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Dependent variable: Asset holdings at the end of period less asset holdings at the beginning of the period.
Independent variables: "d_i:" dummy for $i-$type with $i \in \{SE, TE, SO\}$; $d_i = 1$ if par participant is of type i, zero otherwise.

The main interest, when it comes to timing a bubble, is the anticipation of the drop in the market price. Table 2.8 reports the average amount of changes in the asset holding and how the types differ. Again the semiotic systematically buy the asset, if the asset price goes down in the next period. However, the sophisticated significantly, reduce on average their asset holdings by 0.17 assets in the current period anticipating that the price goes down in the subsequent period. The sophisticated significantly differ in this regard from the technocratic and semiotic types. This indicates, that the sophisticates might be better at solving the timing issue and exit the bubble early and consequent enough, which initiates the fall in the market price.

Willingness to pay and accept: The conceptual framework predicts that TE-types follow a fundamentalist trading-style, SE-types a momentum trading-style, FL-types a noise-trading style and SO-types a bubble-riding trading-style. In order to test for the hypotheses, that all cognitive types follow the same trading strategy H 2.1 - which we want to reject - more rigorously, we use the period-wise individual willingness to pay[64] and accept[65] as a measure for the expected value $E^i(V_t)$. We estimate equation (2.1) separately for each type and compare the estimated coefficients among the types.

Table 2.9: Willingness to pay per type

	FL	SE	TE	SO
FV_t	0.261***	0.174***	0.478***	0.606***
	(0.051)	(0.044)	(0.068)	(0.111)
p_{t-1}	0.799***	0.807***	0.684***	0.549***
	(0.056)	(0.0914)	(0.096)	(0.179)
Constant	-71.95***	-66.482**	-83.592***	-82.887**
	(25.25)	(31.34)	(22.712)	(36.358)
R^2-overall	0.214	0.212	0.318	0.359
N	927	684	586	600

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Willingness to pay for each period
Independent variables: "FV_t:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16 - t) * 24$; "p_{t-1}:" Price in the last period.

Table 2.9 shows that for all types the estimated α_1^i, α_2^i have the expected signs.[66] A higher fundamental value and a higher last period price both increase the willingness to

[64]See table 2.9.

[65]See table B.4.

[66]The Breusch-Pagan test suggests a random-effects model. One can reproduce the same results with OLS with clustered standard errors for robustness.

pay. An F-test rejects the null hypothesis that both coefficients are the same for all possible combinations of types[67], except for the comparison of technocratic vs. sophisticated types and featureless vs. semiotic types. Hence we can reject H 2.1 that any two different cognitive types have the same cognitive model for the price expectation, beside for the two comparison featureless vs. semiotic and technocratic vs. sophisticated types. A closer look at table 2.9 shows that the weights for the fundamental value is larger for the technocratic type than for the semiotic, while the latter puts more emphasis on the momentum component, which gives support for H 2.3. Moreover the difference among sophisticated and technocratic types are reverse to what we expected, the technocrat has a larger weight on the last period price than the sophisticated-type and a lower one on the fundamental value.[68] Taken together, the willingness to buy and the willingness to accept analysis provides weak evidence in support for the differences in the valuation of the asset by each type.

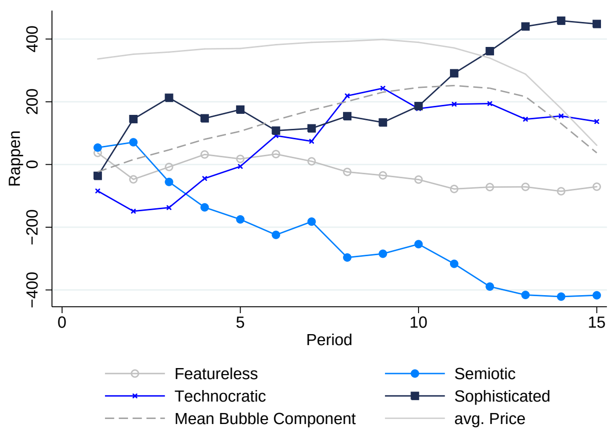


Figure 2.10: Cumulative Trading Gains per Cognitive Type

This figure shows on the y-axis the average cumulative trading gains (, i.e. amount earned from selling assets less amount spend on buying assets up to the current period), per type. In order to compare market dynamics the average market price (grey line) and the average bubble component (, i.e. market price less expected value of the asset) (grey dotted line) are added.

Summary on trading styles: Figure 2.10 summarizes the findings and observation in this trading pattern analysis by plotting the average cumulative trading gains, amount earned from selling assets less amount spend on buying assets up to the current period,

[67] At the 1% level for the pairs: FL vs. TE, FL vs. SO, SE vs. TE, SE vs. SO. The same holds if we include the additional requirement of a common intercept.

[68] In appendix B.11 table B.3, table B.3 and table B.5 we document and discuss results, testing for the differences of the parameters among types, i.e. to reject the null hypothesis that $\alpha_1^i = \alpha_1^j$ or $\alpha_2^i = \alpha_2^j$ for $i, j \in \{TE, SO, SE\}$, we run additional regressions with pairwise comparison of types.

of each cognitive type. The average market price and bubble component has been added in order to compare the cumulative trading gains with the overall market dynamics. The featureless types, on average do not change their asset holdings over time, but increase it a bit in the second half, leading to on average small losses in the trading gains. The semiotic type keeps on building up their asset holding depository and thus generate their large trading losses over the whole 15 periods. The technocrats generate their trading gains in the first 8 to 9 periods and then keep them mainly constant. While the sophisticated sell a bit at the beginning, staying stable in the first half of the market and then increasing their trading gains from period 9-13, the period between the peak of the market price and the peak of the bubble, thus before the market price starts to fall steeply. Figure B.21 in appendix B.11.1 confirms with cash holdings at the end of the period, that sophisticated mainly differ in the timing, when they reduce their asset holding and by how much, which leads to their significant difference in trading gains at the end of the market in period 15.

2.5.3 Market Outcomes

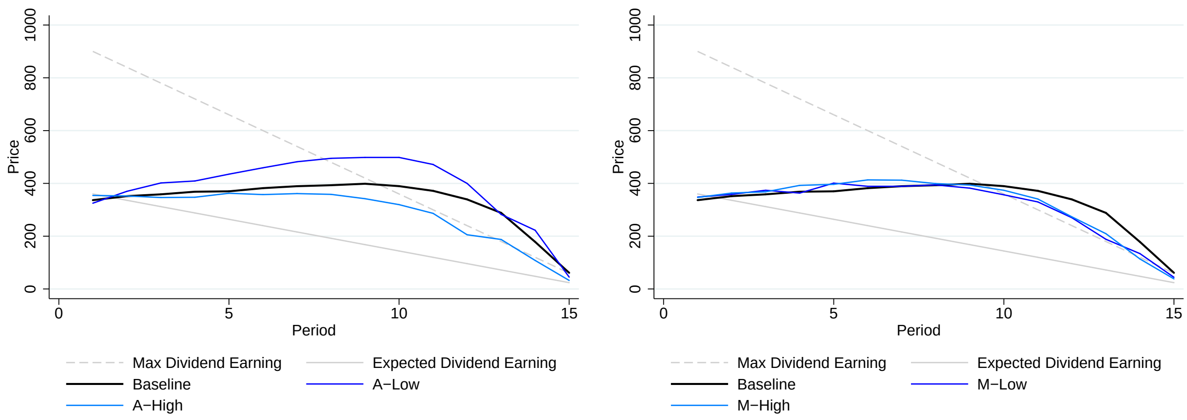
Given the previous results we can conjecture that a higher share of technocratic types will bring the market price closer to the fundamental value whereas more sophisticates will lead to an earlier peak in the market price. Thus the cognitive type composition in the market affects the market price and therefore the size of the bubble.[69]

Result 2.3. *The type distribution affects the market outcome. Particularly, a higher share of A-high types in a market reduces the size of the bubble. We do not find similar effects for the M-dimension. Regression results indicate that differences in market outcomes of the A-segregation seem to be driven by the sophisticated and semiotic types. The no-effect in the M-segregation is the result of offsetting behaviour from the sophisticated and the semiotic types in the same market.*

In order to test how the distribution of types influence the asset market we conducted the segregation treatments, where we split the participants after the first phase according to their performance in the respective dimension. As described in section 2.4, we created markets with participants who tend to score high or low in one dimension, resulting in A-high, A-low, M-high, and M-low markets.

The market outcomes for the split along the A-dimension are plotted in figure 2.11 (a); it compares the average prices (full black line) in the baseline markets with the average market price in the A-low (dark blue line) and A-high (light blue line). In all

[69]Note in the conceptual framework is no specific discussion of how the cognitive types affect the market outcome. Thus the subsequent empirical analysis is more of an empirical observation, then a clear test of a hypothesis from the conceptual framework.



(a) A-Segregation (b) M-Segregation

Figure 2.11: Market Prices in the Segregation Treatments
In both graphs the full black line is the average market price across all markets in the respective treatment, the grey full line is the expected value and the dotted line is the highest possible earnings from the dividends. Graph (a) Light (dark) blue is the average market price in the A-low (high) markets. Graph (b) Light (dark) blue is the average market price in the M-low (high) markets.

three markets, the first one or two periods have market prices below the expected value (grey full line). The A-high markets are closest to the expected value in the first periods, thus show the smallest undervaluation. This deviation pattern remains over the rest of the asset market game (i.e., the average price shows the smallest bubble and remains below the maximum one could earn from the dividend (dotted line)). Those markets with relatively more A- low types show the largest deviation (up- and downwards) from the expected value.[70]

A segregation along the M-dimension, see figure 2.11 (b), did not result in any significant differences among both market types, nor compared to the baseline markets. M-high types act differently depending on the composition of types in the market. Thus it might be that a simple segregation neglects particular interactions among types. In order to test for possible interaction effects, we ran regressions on the market level. The market price, trading volume, the period with the largest deviation of the market price from the fundamental value (peak period) and the size of the largest deviation (bubble max) are the market outcomes we were interested in. As explanatory variables we used the median of A- & M-capacities and the interaction of both capacities in the markets. Table 2.10 reports the results for all periods.

When it comes to the market price, the median analytical capacity does not affect the market price. The higher the median mentalizing capacities in the market the higher is

[70]This observation is in line with the literature that higher average analytically capacities in the market, lead to lower bubbles sizes (Breaban and Noussair, 2015; Cueva and Rustichini, 2015).

Table 2.10: Median cognitive capacities and market outcome

	(1) Price	(2) Volume	(3) Peak Period	(4) Bubble max.
(p 50) A	1.307	0.074*	0.147	4.108
	(1.668)	(0.042)	(0.092)	(4.620)
(p 50) M	4.030*	0.106**	0.074	10.206*
	(2.135)	(0.053)	(0.116)	(5.862)
(p 50) AxM	-0.061**	-0.002**	-0.003*	-0.133
	(0.029)	(0.001)	(0.002)	(0.081)
Constant	211.474*	0.361	7.470	-130.457
	(120.323)	(3.023)	(6.572)	(331.240)
adj. R-squared	7189.78	3093.97	163.60	477.20
N	576	600	40	40

OLS estimator, using clustered standard errors at the market level, robust standard errors in parentheses. For regression (1) and (2) we pooled all periods and markets. Since there is only one largest deviation (3) and (4) only have one result per market. Unit of observation: session.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: " Price:" Market Price; "Volume:" Number of asset traded; "Peak Period:" Period with the largest deviation of the market price from the fundamental value; "Bubble max:" Size of the largest deviation of the market price from the fundamental value;
Independent variables: "(p50) A:" Median of the analytical capacity in the market; "(p50) M:" Median of the mentalizing capacity in the market; "(p50) AxM:" Median of the interaction of analytical and mentalizing capacities in the market.

the market price; while a larger median interaction term between both capacities reduces the market price significantly. If the market median of one of the capacities increases the trading volume becomes larger, whereas the median interaction term reduces the trading volume in the market. The larger the median of the interaction term in the market, the earlier is the peak of the bubble(i.e., the period with the largest deviation from the market price). And finally, the higher the median mentalizing capacity the bigger is the size of the largest deviation of the market price from the fundamental value.

Interpreting these results within the conceptual framework: The more the median participant in the market has a cognitive capacity mix of a technocratic type, the higher the traded volume will be. The more the median participant has a mix of the semiotic type, the higher the market price will be, the more will be traded and the bigger will be the size of the largest deviation of the market price from the fundamental value. The more the median participant has the mix of a sophisticated type, the lower is the market price, the less will be traded and the earlier will the bubble burst. Thus again, the differences in market outcomes of the A-segregation seem to be driven by the sophisticated and semiotic types. Where the former led to an early peak of the bubble in the A-high market and the latter amplified the trend of the market price in the A-low markets. The no-effect in the M-segregation would be the result of offsetting trading behaviour from the sophisticated and the semiotic types in the same market. On the one side the semiotic types follow the trend and tend to make the bubble more extreme. On the other side the sophisticated ride the bubble but are also the ones leading to the burst of the bubble; with more sophisticated in the market, the bubble peak will be earlier, reducing the bubble size. This finally affects the trend following behaviour of the semiotic types.

2.6 Conclusion

Many price patterns observed in real financial markets can only be explained by accounting for heterogeneous behaviour across traders (Boswijk et al., 2007). Creating a framework of heterogeneous behaviour that goes beyond the purely descriptive level, and explains *why* and *how* heterogeneous expectations are formed, is an important challenge to behavioural economics and finance (Hommes, 2011). While there is an important literature on the implications of heterogeneous information for asset markets (Brunnermeier, 2008), heterogeneity in the *perception and processing* of information has received much less attention. It is proposed that even if everyone receives the same information, the processing of this information and thus the perception of it differs among individuals. The source of these heterogeneous perceptions lie in the differences in cognitive capacities.

We started with the working hypothesis that the way humans think about investment decisions is the product of two fundamentally different cognitive capacities: The analytical capacity, A-Dimension, captures a person's grasp of the quantitative aspect of a decision problem, which helps individuals predict the equilibrium outcome of a game; the mentalizing capacity, M-Dimension, is the ability to understand others' beliefs and intentions, which helps to predict their actions. The variation in the level of these two capacities led to different perceptions of the decision situation and thus heterogeneous behaviour.

We applied this hypothesis to a decision situation of an investor and discussed in a simple conceptual framework how the two independent cognitive capacities influence expectation formation and thus leads to heterogeneous behaviour in asset markets. The basic notion is that a deficit in either dimension led to a systematically distorted cognitive model of future price developments, which in turn biases willingness to pay for an asset and willingness to accept an offer as well the traded quantity. Most importantly, a single dimension alone is insufficient to explain the observed behaviour. In order to provide a simple conceptual framework for how these cognitive capacities affect the behaviour, we use four stylized cognitive types: The featureless type (FL) lacks both capacities and we expect this cognitive type to have an unsystematic trading style. The technocratic type (TE) has strong analytical capacity but lacks mentalizing ones. This type will be able to identify the fundamental value of the asset and avoid trading losses. The semiotic type (SE) possesses high mentalizing capacities and has poor analytical capacities. This type will identify the systematic (upward) trend of the market price, but has difficulties in recognizing the departure from the fundamental value, which leads to late exit and heavy losses. Only the sophisticated type (SO), who has both capacities, will identify the systematic departure from the fundamental and anticipate the eventual return of the price to the fundamental value. Based on this framework we derived the testable predictions that there is a mapping from each cognitive type to one of the following trading styles: fundamentalist- (TE), momentum-trading (SE), noise trading (FL) and bubble riding (SO).

Our experimental approach allows us to test these predictions in a tightly controlled environment, where we can measure each trader's two dimensional cognitive capacities mix independently and observe their trading behaviour in a simple experimental asset call-market with exogenously imposed fundamental values. The empirical findings can be summarized in three key results: (1) Analysing the trading gains of the asset market, we observe that the four cognitive types achieve different outcomes. While sophisticates realize the largest trading gains, the semiotic types face the largest losses. We found barely notable differences among the featureless and technocratic types in terms of trading gains. Thus, focusing on just one of the two dimension masks important heterogeneity across cognitive types. Being better at only one cognitive capacity does not increases trading gains. Moreover, a one-sided specialization on mentalizing capacities leads to substantial losses. (2) These differences in trading gains are the result of heterogeneous trading patterns. While the technocrats and semiotic types have opposed trading strategies, with the former following a fundamentalist approach and the latter act as momentum traders. The sophisticated behaves like a bubble rider and is significantly better at timing the exit of the bubble, before the market price declines strongly. (3) On the market level we found that a higher share of A-high types reduce the bubble size, while there is no effect if the share of M-types becomes larger. The differences in market outcome in the A-segregation seem to be driven by the trading behaviour of the sophisticated and semiotic types. Where the former led to an early peak of the bubble in the A-high market and the latter amplify the trend of the market price in the A-low markets. The no-effect in the M-segregation is the result of offsetting behaviour from the sophisticated and the semiotic types in the same market.

In sum our results uncover a structure that was hidden in previous, one-dimensional approaches that mostly aimed at the analytical dimension of cognitive capacities (e.g., performance in beauty contest as measure for strategic sophistication (Bosch-Rosa et al., 2015; Camerer and Ho, 2015)). The bottom line is that heterogeneity in cognitive capacities translates into heterogeneity in behaviour and being better in one dimension does not compensate for a lack in another dimension on the behavioural level. In terms of the experimental asset market: Being good in either analytical or mentalizing capacity does not translate into higher trading gains, but can in fact be highly detrimental to profits. We think that such interaction effects between both dimensions also appear to (economic) decision situations beyond the asset market application. Another avenue to take, is to test our findings in the field.[71] Overall, understanding market dynamics and why certain groups react the way they do, might help to better target policy measures that may mitigate the rise of miss pricing in financial markets.[72]

This paper contributes to the discussion on skills of traders, by highlighting the interaction of two cognitive capacities influencing trading decisions. Success in financial markets is not pure luck but also the result of exercising the right cognitive capacities. Making trading become a gamble if one lacks one of the necessary capacities to fully understand the decision situation.

[71]Thus classifying real portfolio manager and small private investors according to the first phase of our experiment and compare the returns in their portfolios. This might help to improve performance by adjusting selection mechanisms for professional traders by institutional investors and nudging private investors if they show tendencies for a certain behaviour, by highlighting certain information, they tend to neglect.

[72]While technocrats and sophisticated do react on a certain information, semiotics might have difficulties to decode the information and find an optimal response to it.

3 Re-examining the effects of risk attitude and over-confidence on trading behaviour within experimental asset markets

3.1 Introduction

Investors risk-aversion (Geanakoplos, 2010) and over-confidence (De Bondt and Thaler, 1995) are among the most common explanations when it comes to anomalies on financial markets, such as deviations of the asset price from the fundamental value or excess trading volumes. In order to test the influence of these trader characteristics on trading behaviour one has to both measure these characteristics and to observe the trading behaviour. Laboratory experiments are well suited for such tests, since they allow to assess separately participants characteristics and the trading behaviour. Furthermore, one can control the trading environment and market size, knows the fundamental value and the characteristics of all other market participants. Experimental studies examining the influence of either risk-aversion or over-confidence rely either on a small number of participants, or markets, or both. Furthermore, some of the studies changed the size, the length of the markets or the incentive scheme; implying even fewer observations per treatment. This manuscript takes advantage of a big dataset of 40 experimental asset markets which last for 15 periods and uses the same underlying random dividend stream.[1] Moreover, in contrast to the other experimental studies, all markets are large with 16 participants (N = 640 participants total), mitigating the market power of a single trader. This is a broad data basis to re-examine the role of risk-aversion and over-confidence and to check the robustness of previous results. In a first step, some definitions of risk-aversion and over-confidence are given to clarify and structure the used concepts in this manuscript.

Risk-aversion: In everyday speech a person is considered to be risk-averse if this person prefers an outcome with some uncertainty to an outcome with more uncertainty but a higher expected value. In economic terms, risk-aversion is usually defined by a decision maker who considers owning the expected outcome of a lottery to be at least as good as

[1]The 40 markets experienced one of three different treatments. For a description of these treatments see section 2.4 of chapter 2.

participating in this lottery.[2] This definition leads to several measures of risk aversion based on choosing among lotteries (Dohmen et al., 2010; Eckel and Grossman, 2008; Holt and Laury, 2002). Even though such measures deliver precise rankings among subjects, they might be to narrow (i.e., they might be only applicable to a specific set of situations where risk arises from an uncertain but known source(Ang et al., 2010)). A more holistic approach for the measurement of risk-aversion is to understand risk-aversion as a personality trait and thus, to use subsets of self-reported questions of personality questionnaires, as it is often done in psychology.[3] In this study we use both approaches and find similar results. Yet, patterns are more robust for the measures which are based on the self-reported questions.

Over-confidence: Following Moore and Healy (2008) over-confidence can be classified into three categories, depending on to whom a participant is comparing his or her abilities and how these are measured. First, over-confidence in the sense of over-estimation means that a person over-estimates his or her own "abilities, performance, level of control or chances of success"(Moore and Healy, 2008, p.3). If for example a student believes that his or her grade in an exam will be 4.0, while it is lower in reality, one would call this over-estimation. This type of over-confidence is also known as miss-calibration. Second, over-confidence in the sense of over-precision means that a person believes to make less errors than it is actual the case. This makes people believe their judgements to be correct in more cases than it is actually the case (Alpert and Raiffa, 1982; Lichtenstein et al., 1977). Usually miss calibration is measured by asking participants to assign a probability to any of their answer hat their answer is correct. Third, over-confidence in the sense of over-placement makes participants think that they are better than others. For example 90% of US car drivers believe themselves to be a safer and more skilled driver than the median driver in the US (Svenson, 1981). This phenomenon is also known as "the-better-than-average-effect". In the subsequent analysis I will use an over-placement measure. In what follows I refer to this measure as relative over-confidence.

The set-up of the experiment consists of two phases: In the first phase, the individual participant characteristics were elicited. Risk-aversion was obtained in two distinct ways: First, by the Holt-Laury task giving participants 20 choices between a certain outcome and a risky lottery (Holt and Laury, 2002). While the risky lottery remains fix over all 20 decisions, the certain outcome increases from the first to the last decision. The number of risky lottery choices over the certain outcome yields the measure of risk-attitude of a par-

[2]See Definition 6.C.1 in Mas-Colell et al. (1995).

[3]Such as: When it comes to driving a car, on a scale from 0 (very cautious) to 10 (very risk taking) how would you judge your risk behaviour?

ticipant. Second, by asking them self-reported questions on their everyday risk-attitude. Relative over-confidence was measured by the respondent's assessment of his or her relative performance (in quintiles) compared to other participants. The deviation between the expected quintile and the real quintile yields the degree of relative over-confidence. In the second phase, we let the participants trade a single asset in an experimental asset market. Each share of the asset paid out a random dividend with an expected value of 24 Rappen in each period. In these type of markets the market price tends to be above the fundamental value (i.e. a bubble).

The main results of the experiments are:

Risk-aversion: At the individual level no risk-aversion measure correlates with the final pay-off from the experiment, the offered numbers of assets to buy, or the offered prices to sell. Nevertheless, the offered buy price declines over all periods when participants are more risk-averse in career matters. However, participants choosing more often the lottery over the certain outcome in the Holt-Laury task tend to offer lower buy prices, once the bubble bursts. This effect is weakly significant. During all 15 periods, more risk-averse participants tend to offer less assets to sell, hold fewer assets, make less often bid- and sell-offers and are involved in fewer successful trades. While these effects are small in size for the whole market, the effects become stronger after the peak of the bubble. In particular, in the final period one can speak of a considerable effect of the risk-measure.

At the market level, there is a correlation between the risk-measures and the trading volume for all 15 periods. However, the higher the average number of risky-choices in the Holt-Laury-task, the higher is the trading volume in the final period. The market price tends to be lower, if the average risk-aversion is lower in the market. Again, this effect is mainly driven by the periods after the peak of the bubble.

Relative Over-Confidence: At the individual level, there is no correlation between the relative over-confidence measure and the final pay-off from the experiment. The only (weakly) significant effect is that relatively over-confident participants offer more assets to sell after the peak of the bubble. The weak significance of the effect raises the question on multiple-testing and whether there are correlations among relative over-confidence and individual trading behaviour.

At the market level, I find that market with, on average, higher relative over-confident participants, tend to have a higher trading volume. The trading volume is particular large once the bubble burst. Furthermore, markets with an higher average of relative over-confidence experience higher market prices, in particular, around the peak of the bubble.

The remaining manuscript is structured as follows: Section two provides a literature overview focusing on results from experimental studies. In section three, theoretical hypotheses are derived within a classic noisy rational expectation framework. Section four describes the experimental design and section five discusses the empirical results. Finally section six discusses the findings and concludes this manuscript.

3.2 Literature Review

Since Smith et al. (1988) the number of experimental asset market studies which aimed at explaining financial market anomalies by individual trader characteristics exploded. In this literature review, I restrict the focus to studies on the effects of risk attitude and over-confidence on trading behaviour in experimental asset markets. The interested reader is referred to Palan (2013) and Powell and Shestakova (2016) for a broader review on the current state of research using experimental asset markets.

Risk-attitude: Ang et al. (2010) argue, similar to Geanakoplos (2010), that heterogeneity in risk attitudes can lead to price movements and that therefore prices can deviate from the fundamental value. They test this hypothesis within 14 oral-double auction markets with around 12 participants in each lasting over 10 periods; each market varies either in the group composition, task of the participant (e.g. investment horizon, tournament structure etc.) or initial endowment. Risk attitudes are elicited based on a subset of questions of a psychological personality inventory test (Jackson, 1976), and only those participants with the lowest/the highest risk aversion were invited to participate in the experimental asset market. Their main result is that less risk-averse participants tend to speculative trading strategies and trade at higher prices on average.

Fellner and Maciejovsky (2007) use data from four blocks of continuous double auction experimental asset markets with overall 26 markets and 280 participants. The blocks vary by the number of periods (13-18), the subjects per market (8-12), the initial assets (5-8) and the initial cash endowment (250-300 in experimental currency units). The risk attitudes are derived based on a Holt-Laury task with seven decisions, where participants had to choose between a risky binary lottery and a certain outcome. One of the decisions was implemented randomly. The main finding is that the less risk averse participants are, the higher the total market activity, the offers made, and the number of successful trades.

Breaban and Noussair (2015) conducted 16 sessions of experimental asset markets, which lasted 15 periods and had 7-9 participants in each market. Each market had a flat fundamental value in periods 1-8. In periods 7-15 half of the markets had an increasing fundamental value, while the other of the markets had a falling fundamental value. Risk attitudes are assessed by a Holt-Laury task. The main results are: First, the higher the average risk-aversion in the market, the lower the price level in markets with increasing fundamental value. Second, at the individual level more risk averse participants tend to sell more units, trade close to the fundamental value and are also less likely to behave like a momentum trader.

Eckel and Füllbrunn (2015) analyse 12 markets with 9 participants in each market, but varying gender composition in each market. Risk-aversion is elicited by a Holt-Laury task using 6 lottery options that vary in risk and expected return (Eckel and Grossman, 2008). The main finding is that markets with more risk-averse subjects tend to experience smaller bubbles. This effect, however, is difficult to disentangle from the gender effect induced by the group composition of the markets in the experimental design of Eckel and Füllbrunn (2015).

Over-confidence: Kirchler and Maciejovsky (2002) investigated six experimental asset markets with 12 participants each, measuring over-confidence by (a) over-precision and (b) over-estimation tasks. Michailova (2011) investigated ten experimental asset markets with 6 participants each; over-confidence was measured by over-precision tasks.[4] Both studies show that markets with a significant proportion of highly over-confident participants experience both larger bubbles and trading volume.

Smith (2012) conducted 6 experimental markets with 6 participants. Over-confidence was measured by using (a) over-estimation and (b) over-placement tasks. The main findings are: First, over-confident traders do not trade more than other traders, but they might perform better. Markets with on average higher over-confident participants show higher trading volumes, but no effect on the market price was found.

Oechssler et al. (2011) run in 18 sessions a continuous double auction market with 3 rounds, each round consisted of 10 real trading days, 10 participant and 5 assets to trade in each market. Over-confidence was measured by using an over-placement task.[5] They find that an increase in the median over-confidence increases the probability of bubbles.

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[4]I.e. letting participants answer 18 quiz questions and ask them about their confidence that the answer is correct in percentage points. A bias score can be calculated by subtracting from the average percentage confidence the average of correct answers.

[5]Over-confidence was operationalized by asking participants before each round to rank themselves among the 60 other participants of the treatment in terms of payout after the round.

3.3 Hypothesis formation

This section derives hypotheses based on a discussion on the influence of risk-aversion and over-confidence within the standard competitive rational expectation model with heterogeneous information (Grossman, 1976; Hellwig, 1980). The derivation of the canonical framework with traders competing in demand schedules follows Ch. 4.2 of Vives (2010).[6]

3.3.1 Model and risk-aversion:

Assume an economy with a single risky asset, with random liquidation value $\tilde{\theta}$ which is normally distributed with mean $\bar{\theta}$ and variance $\frac{1}{\tau_\theta}$.[7] The economy is populated by informed traders and noise traders, where the aggregated trade volume of the latter is assumed to follow a random variable $\tilde{u}$ with mean zero and variance $\frac{1}{\tau_u}$.[8] The informed risk-avers traders, indexed on the interval $i \in [0,1]$ with the Lebesque measure, derive their utility from the return function $\Pi_i = \left(\tilde{\theta} - p\right) x_i$ of buying x_i shares of the risky asset at price p. The utility function is of CARA-type $U_i(\Pi_i) = -e^{-\rho_i \Pi_i}$, where $\rho_i > 0$ is the CARA coefficient.[9] The non-random initial wealth of the traders is normalized to zero. Each trader $i \in [0,1]$ receives a signal s_i about the ex-post liquidation value $\tilde{\theta}$, specifying the signal as $\tilde{s}_i = \tilde{\theta} + \tilde{\epsilon}_i$; the errors,$\tilde{\epsilon}_i$, have mean zero and variance $\frac{1}{\tau_\epsilon}$. Moreover, they are uncorrelated across traders and uncorrelated with the noise trading volume, $\tilde{u}$, and the liquidation value $\tilde{\theta}$. The traders can condition their trades on the price and their private signal s_i, thus the information set of trader i is $\{s_i, p\}$. The distributional assumptions are common knowledge among all traders in the economy. The analysed equilibrium is a symmetric one, in which all traders play the same strategy.[10] The best response for any arbitrary signal s_i and price p is given by:[11]

$$x_i\left(s_i, p\right) = \frac{\mathbb{E}(\tilde{\theta}|s_i, p)}{\rho_i \mathrm{Var}(\tilde{\theta}|s_i, p)} \tag{3.1}$$

From 3.1 one can derive the first testable hypothesis.

[6] Different to Vives (2010), I consider the special case that all traders are informed and receive a signal about the liquidation value of the asset. Thus in terms of Vives (2010) the fraction of informed traders is $\mu = 1$.

[7] One can think of a fundamental value.

[8] The expected volume of noise trading $E\left(|u|\right)$ is proportional to the standard variation $\frac{1}{\sqrt{\tau_\theta}}$. See footnote 10 in Vives (2010) Ch. 4.2.

[9] Note a higher ρ_i implies a higher risk-aversion and ρ_i^{-1} can be interpreted as the risk tolerance of the trader.

[10] See Vives (2010) pp. 114, for a formal definition of this type of equilibrium within this framework.

[11] Vives (2010) pp.116.

Hypothesis 3.1 (**Individual Valuation and Risk-Aversion:**). *If agent j has a higher risk aversion than agent i, i.e. $\rho_j > \rho_i$, and both have the same information set $\{s_j, p\} = \{s_i, p\}$, then agent j will trade less than agent i.*

For the derivation of the market equilibrium Vives (2010) assumes, that all traders have the same risk-aversion, i.e. $\rho_i = \rho \ \forall i \in [0, 1]$. Moreover, traders understand the relationship between the underlying uncertainty $(\tilde{\theta}, \tilde{u})$ and prices. The informed traders use a demand schedule strategy (i.e. upon reception of their private signal, traders submit their demand schedules contingent on the private signal). Once the price is realized, the amount the agent wants to invest into the risky asset is $x_i(s_i; p)$. Thus trader i's strategy is a mapping from his private signal to the correspondences of demand functions, $x_i(s_i; \cdot)$. In addition, noise traders place their orders and then an auctioneer finds the market clearing price.[12] Using standard methods[13] one can characterize the linear Bayesian equilibria of this demand function game by:

$$x_i(s_i; p) = \rho^{-1}\tau_\epsilon (s_i - p) - \frac{\tau_\theta}{\rho + \tau_\epsilon \tau_u \rho^{-1}} \left(p - \bar{\theta}\right). \tag{3.2}$$

In this equilibrium, informed traders have two reasons to trade: First, they can speculate on their private information with a responsiveness of $\rho^{-1}\tau_\epsilon$ (perceived noise trading motive). Second, they sell (buy) more of the asset if the price is above (below) the prior expectation of the asset value, which corresponds to the typical behaviour of a market maker. The intuition for this behaviour is that even if the traders are informed, due to their noisy signal they do not fully know whether price changes are motivated by other informed traders or by noise traders. The expected aggregate volume traded by the informed traders is given by:[14]

$$\mathbb{E}\left[\left| \int_0^1 x_i(s_i; p) di \right| \right] = \sqrt{\frac{2}{\tau_u \pi}}. \tag{3.3}$$

Hypothesis 3.2 (**Expected Trading Volume and Risk-Aversion**). *The risk-aversion of traders in a market, ρ, does not influence the expected trading volume in the market.*

While it might be counter-intuitive, that risk-aversion can affect a single agents decision and not the whole market, one has to keep in mind that on the aggregate and in

[12] If there are multiple market prices, then the one with minimum absolute value will be picked, if there is also a negative price with the same absolute value the positive price will be chosen. If there is no market-clearing price, the market shuts down and the auctioneer sets a price equal to $\pm\infty$ leaving the traders with infinitely negative utility.

[13] See Vives (2010), pp.117, for details of the derivation.

[14] See Vives (2010) pp.121 for details of the derivation.

expectations the speculation motives of all informed traders can cancel out each other. Thus, the motive only for market-making is left (i.e. counterbalancing the noise trading).

The equilibrium market price in this linear Bayesian equilibrium is given by:[15]

$$P\left(\tilde{\theta}, u\right) = \bar{\theta} + \lambda^{-1}\left(\tau_\epsilon \rho^{-1}\left(\tilde{\theta} - \bar{\theta}\right) + \tilde{u}\right). \quad (3.4)$$

The parameter $\lambda^{-1} = \frac{\rho + \tau_\epsilon \tau_u \rho^{-1}}{\tau_\epsilon + \tau_\theta + \tau_u \tau_\epsilon^2 \rho^{-2}}$ is also known as the market depth, i.e. the impact on the market price if the trading volume moves by one unit. If a market can absorb a large trading volume without moving much, then this market is classified as a deep market.

Hypothesis 3.3 (**Market Price and Risk-Aversion**). *The higher the risk-aversion of traders in a market, ρ, the lower the relative weight, $\tau_\epsilon \rho^{-1}$, on the signal of the fundamental value, when compared to the noise trading, $\tilde{u}$.*

From equation 3.2, we know that the propensity to trade on the private signal, $\rho^{-1}\tau_\epsilon$, declines in the risk-aversion of the traders. Thus, they are less willing to exploit their private information, when they are more risk averse, which reduces the informativeness of the market price. Therefore, loosely spoken, the more risk-averse the market participants, the less will the market price track the fundamental value.[16]

3.3.2 Relative over-confidence:

Similar to the broad meaning of over-confidence, there exist several approaches of how to model them. Most of these approaches focus on over-confidence in the sense of over-estimation or over-precision. Kyle and Wang (1997) and Odean (1998) incorporate over-precision in the trading model framework of Kyle (1985)[17] and Hellwig (1980).[18] They do so, by assuming that an over-confident trader differs in his perception of the precision of his private signal $\hat{\tau}_\epsilon^{-1}$. Thus, the trader perceives $\hat{\tau}_\epsilon^{-1} < \tau_\epsilon^{-1}$.

In this manuscript the measure used is a relative over-confidence task.[19] In the spirit of Kyle and Wang (1997) and Odean (1998), one can interpret this relative over-confidence as the perception of these agents that other agents are not as good as they are. Thus,

[15]See Vives (2010) pp.117 for details of the derivation.

[16]See Vives (2010) p.121 for a detailed discussion on the informativeness of the market price.

[17]Kyle and Wang (1997) show in their theoretical framework of rational speculation, that such miss-calibrated traders generate higher expected profits than the rational opponent and that such traders can persist and survive in the market in the long-run.

[18]Odean (1998) shows that higher miss-calibration of the traders implies a higher trading volume, higher price volatility, less price quality and a lower expected utility.

[19]Thus subjects think they rank higher with their own performance relative to the others, then its actual the case. E.g.: They think of them-self to belong to the best 20% in a group, even though they belong to the middle 20%.

agents perceive a higher noise trading activity in the market (i.e. their perceived noise-trading $\hat{\tau}_u^{-1}$ is larger than the actual τ_u^{-1}). Hence, a larger perceived noise-trading activity, $\hat{\tau}_u^{-1}$, can be interpreted as higher relative over-confidence. The following hypotheses are the result of comparative statics with respect to τ_u^{-1}.

Hypothesis 3.4 (**Expected Trading Volume and Relative Over-Confidence**). *The higher the perceived noise-trading $\hat{\tau}_u^{-1}$ in a market, the larger is the expected trading volume in the market (see equation 3.3).*

Equation 3.2 shows that the speculation on the private signal, $\rho^{-1}\tau_\epsilon$, remains unaffected by larger perceived noise trading. However, the market making motive, decreases in $\hat{\tau}_u$ and so does the perceived need to counterbalance the noise trading.

Hypothesis 3.5 (**Market Price and Relative Over-Confidence**). *The relative weights between changes in the fundamentals and noise trading in the equilibrium market price remain unaffected by the perceived noise-trading, $\hat{\tau}_u^{-1}$, in the market (see equation 3.4).*

The higher expected trading volume in the market increases the market depth (i.e. λ^{-1} is lower). However, the change in market depth affects market price changes due to changes in the fundamental value as well as the noise traders demand (see equation 3.4). The relative weights among both components remain unaffected by a change in the perceived noise-trading activity, $\hat{\tau}_u^{-1}$. Consequently, it is unclear, whether markets with higher relative over-confident participants are more or less informative and thus track closer or depart further from the fundamental value.

3.4 Experimental Design

The experimental sessions from chapter 2 also elicited risk-aversion and over-confidence, providing a large data basis to test the influences of risk-aversion and over-confidence on trading behaviour and observe trading behaviour independently. Thus, the procedure in the sessions and the asset market are the same as described in section 2.4 of chapter 2. In the following, I only describe the tasks measuring risk-preference and relative over-confidence.[20]

3.4.1 Risk-Preference Task

Risk-preferences are measured by a standard Hault-Laury lottery task and several self-reported questions asking the subjects to judge their risk-perception in specific real-life situations.

[20]For a description of the other tasks refer to section 2.4 of chapter 2

Holt-Laury lottery task: Risk-aversion was assessed by a choice task similar to Holt and Laury (2002). The participants are confronted with a decision table with 20 decisions to make between option A receiving a fix amount and option B a lottery with CHF 0 or CHF 30 as equally likely outcomes. Each decision was presented in one row and the certain amount increased from row to row, while the lottery was always the same. At the end of the session, the computer randomly draw one of the 20 rows and implemented the choice in this row, thereby determining the subjects payments in this task. This approach allows us to determine the certainty equivalent of the subject and, thus, to compare the degree of risk-aversion across subjects. The resulting variable is called *[# Risky Choices]*.[21] The higher this variable, the less risk-averse was the choice made by the participant in this task.

Dohmen et al. (2010) find that individuals with higher analytic capacities, measured by two sub-modules of the Wechsler Adult Intelligence Scale, take significantly risk in the Holt-Laury lottery task, this relation is independent from age and sex. This is in line with recent work on the subjective component of risk perception (e.g., Andersen et al. (2014); Harrison et al. (2015)).[22]

Self-reported questionnaire: As an alternative measure for risk-preferences, a self-reported questionnaire was used. Questions concerning risk preferences were included together with the additional questions in an exit questionnaire at the end of the experiment. To elicit risk preferences participants were asked to answer a couple of self-reported questions which would describe themselves. The most relevant for the analysis in section 3.5 are reported here:[23]

- You can behave differently in different contexts. How would you assess your willingness to take risks in the following areas? *[All questions had a scale from 0 (try to avoid risks) - 10 (fully prepared to take risks))]*
    - With financial matters? *[risk3]*
    - With your professional career? *[risk5]*

Thus, the higher *risk 3* and *risk 5* the lower is the self-reported risk-aversion in this particular matter.

[21]Detailed instructions and the computer screen can be found in the appendix B.4.7.

[22]Therefore, the evaluation of the consequences between a lottery and a certain amount might be more clear to a participant with higher analytic capacities.

[23]Note we also asked further questions on the risk-attitude that can be found in the appendix B.8. Since these measures did not showed any robust effects, we do not analyse them further.

3.4.2 Over-confidence Measure

Together with the Raven's Matrices non-verbal IQ-Test[24] we measured over-confidence, by asking the subjects after the Raven's Test: "Which group do you think you belong to?"; with "Best 20%", " 20% immediately below the best 20%", "Middle 20%", "20% immediately above the worst 20%" and "Worst 20%" as options to answer; thus corresponding to the five quintiles.[25] The relative over-confidence measure, OCrel, is constructed by subtracting the estimated quintile, Qestimated, from the actual quintile of correct answers, Qperformance. Both quintile measure can be either 1,2,3,4 or 5 with 1 corresponds to the best 20% and 5 the worst 20%.[26]

$$OCrel = Qperformance - Qestimated \tag{3.5}$$

Thus, if OCrel is zero, the estimated quintile coincides with the performance quintile; if OCrel is positive (negative), the subject over (under)-estimates its quintile. The main drawback of this measure is that eventually not all subjects can be classified due to the limitation on its borders: In the most extreme case a very over-confident subject answering all (no) questions correctly can not be classified to be over (under)-confident according to this measure.[27]

Table 3.1: Summary Statistics

Measure	Mean	SD	Min/Max
# Risky Choices	11.78	3.89	0/20
risk3	2.90	2.19	0/10
risk5	4.86	2.61	0/10
OCrel	0.90	1.38	-4/4
Age	23.16	3.44	17/47
Gender	0.50	0.50	0/1

N=640, *# Risky Choices, OCrel, risk3* and *risk5* are as described above; "Age": Self-reported age of the subject; *"Gender"*: dummy variable, 1 if the subjects reports to be female and zero otherwise.

Table 3.1 reports the summary statistics of the risk-aversion and the over-confidence

[24]The appendix provides a more detailed description (including instructions) for Raven B.4.1.

[25]The screen can be found in the appendix B.4.2.

[26]Subjects having 7 or less correct answers in the Raven's Test belonged to the worst 20%; those with 8 correct answers belonged to the second worst quintile; those with 9 correct answers belonged to the middle quintile; subjects with 10 answers belonged to the second best quintile and those with 11 or 12 correct answers belonged to the best quintile.

[27]Which might partially explain the high negative correlation between the analytical dimension from chapter 2 and OCrel, ($\rho = -0.3411$, $p - value < 0.01$).

measures, gender, and age. On average, the participants are 23 years old; 50% of them are female. At the Holt-Laury task participants started on average to prefer the save outcome over the risky-lottery at CHF 12 which is lower as the expected value from the lottery offered. The relative over-confidence measure, *OCrel*, indicates a slight overconfidence on average.

Table C.1 in the appendix C.1 shows the correlation among all measures. The *# Risky Choices* is weakly positive correlated with analytical capacities[28],*risk3* and *risk5*; *# Risky Choices* and *gender* are negatively correlated. Most self-reported risk-measures are positively correlated with each other[29] indicating that, they measure a similar characteristic of the subjects. *OCrel* is negatively correlated with analytical capacities and slightly positively correlated with *age*.

3.5 Results

This section discusses the results from the laboratory experiments for the risk aversion measures (section 3.5.1) and over-confidence measures (section 3.5.2). Each of these subsections is divided into particular time periods of the experimental asset market (All-, 1st-, before the bubble peak -, after the bubble peak-, 15th-period(s)). While it is obvious to examine all periods, I also take a closer look on the period one, for two reasons: First, some researchers speculate that the first period market price is below the expected value, due to risk-averse participants (Palan, 2013). Second, due to the lack of a prior market prices the participants have no information about the value expected of others. Since the influence of risk-aversion and over-confidence might differ throughout the formation of a bubble and after its crash, I separately analyse the periods before and after the peak of the bubble, i.e. the period with the largest deviation of the market price from the fundamental value. Finally, I also take a closer look on the final period, because after the period fifteen the asset can not be traded any more (i.e, only the risky nature of the dividend determines the value of the asset).

Individual trading behaviour is measured by the following outcome variables of individual decisions made during the asset market: Offered Buy- and Sales Prices as well as the numbers of assets offered to buy and sell; the number of assets hold at the end of the period; the change in the assets inventory from the beginning of the period to the end of the period and participation in the period (i.e., whether the participant made a sell or an buy offer). Moreover, I analysed the effect on outcomes at the market level and used as outcome variables: The market price, the trading volume, the period of the bubble

[28]As measured in chapter 2.

[29]Except for risk8 to risk4, risk5, and risk6

peak and the size of the largest deviation of the market price from the fundamental value (Bubble Max).

To present the results in a compact manner, the regression coefficients of the regressions are summarized in tables 3.2 to 3.5. The full set of regression results is shifted to in the appendix C.2 and C.3.

3.5.1 Risk-aversion

Result 3.1. ***Risk-Aversion: Individual Trading Behaviour***
There are a few significant results of the risk-aversion measures on the outcome variables at the individual level: More risk averse participant have a lower likelihood to make buy- and sell offers, offer lower prices to buy the asset, offer a lower number of assets to sell, hold less assets and is less often involved in successful trading. The majority of results hold for the self-reported willingness to take financial or career risk measures but not for risk-aversion measured by the Holt-Laury task. Nevertheless, these effects are small in size and mainly driven by periods after the peak. In particular, in the final period, the above mentioned effects of risk aversion become stronger in size and the significance level increases. No effects on any of the outcome variables are found in the first period. Neither of the risk measures has an impact on the final earnings from the asset market.

Table 3.2 and Table 3.2 summarize the estimation coefficients obtained from separate OLS regressions of the individual trading behaviour variables and the risk-measures and individual characteristics (age and gender), respectively. The discussion of the results will refer to the respective tables in the appendix C.2.

All periods: There is a small effect between the offered buy-price and the self-reported risk-attitude in professional career (risk5)[30]. If risk5 increases by one unit, the offered buy price is 1.86 Rappen higher. The mean of all offered buy prices is 250 Rappen (SD:134.4), thus the size of the effect is not very high and only significant on the 10% level. There is not effect of any risk-aversion measure on the offered number of assets to buy[31] or offered sell-price[32]. The less risk averse the participant are in the Holt-Laury-Task (# Risky Choices) the more assets they offer to sell.[33] While this effect is highly significant, the magnitude of the effect is not very large with 0.05 assets more offered to sell for one unit increase in the Holt-Laury-task; considering that on average 2.2 (SD: 2.04) assets were offered to sell. The assets hold at the end of the period increases if the participant

[30]See table C.2 column (4).
[31]See table C.4 columns (1,3,4).
[32]See table C.3 columns (1,3,4).
[33]See table C.5 column (1).

is less risk-averse in the self-reported risk-attitude in financial decisions (risk3).[34] A one point increase in the risk3 measure increases the number of asset hold by 0.07. Given that on average, the participants hold 2.5 (SD: 2.78) assets, the size of this effect is small. Participants self-reporting less risk-aversion in risk3 and risk5 tend to build up their asset holdings over all periods (Asset changes).[35] But again with a small effect size of an 0.001 increase if the risk3 and risk5 measures go up by one unit. On average the number of asset changes is zero with a standard deviation of 1.46. Furthermore the less the self-reported risk-aversion in risk3 and risk5 the more often these participants make a buy- or a sell offer in the market.[36] On average 0.91 (SD: 0.28) participants make a buy- or a sell offer in a period. There are no effects from any risk measure on the cash holdings at the end of the asset market, and thus on the earnings from this task.[37]

1st period: The only effect in the first period is that participant who have a low self-reported risk-aversion in financial matters (risk3), tend to offer more assets to buy. Otherwise, there are no effects between the risk-measures and any of the outcome variables.[38] Hence the explanation that the market price is below the expected value due to risk-averse participants in period 1, is not supported.

Periods before the peak of the bubble: The offered buy price is higher, the lower the self-reported risk attitude in career matters (risk 5).[39] The effect size is small and weakly significant. The number of assets offered to sell is significantly higher if the participants made less risk-averse choices in the Holt-Laury task.[40], with a small effect size wise. The higher the risk aversion in career matters, the lower the likelihood to participate in the market by making an buy- or a sell-offer.[41] There are no effects of risk measures on the offered numbers of assets to buy[42], the offered price to sell[43], the number of assets hold at the end of the period[44] and the number of successful bought or sold assets.[45]

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[34]See table C.6 column (3).

[35]See table C.7 columns (3,4).

[36]See table C.8 columns (3,4).

[37]See table C.37 columns (1,3,4).

[38]See tables C.9 to C.15 columns (1,3,4).

[39]See table C.16 column (4).

[40]See table C.19 column (1).

[41]See table C.22 column (4).

[42]See table C.18 column (1,2,4).

[43]See table C.17 column (1,2,3).

[44]See table C.20 column (1,2,4).

[45]See table C.21 column (1,2,4).

Table 3.2: Overview of the OLS coefficients estimate on risk measures (Individual Trading Behavior I)

Dependent Variable	Risk Measure	Periods All	Period One	Periods Before Peak	Periods After Peak	Period Fifteen
Buy Price	# Risky Choices	0.38	-0.14	0.84	**-1.85***	**-1.65***
		[-1.28,2.03]	[-2.70,2.42]	[-0.76,2.44]	[-4.05,0.36]	[-3.56,0.27]
	risk3	2.25	-1.62	1.88	2.04	0.86
		[-0.68,5.19]	[-6.30,3.06]	[-0.95,4.72]	[-1.87;5.95]	[-2.35,4.06]
	risk5	**1.86***	0.08	**1.80***	2.78	-0.06
		[-0.29,4.00]	[-3.15,3.30]	[-0.28,3.88]	[-1.12,6.68]	[-1.97,2.86]
Buy Volume	# Risky Choices	-0.57	-1.17	0.03	-2.80	-4.01
		[-2.20,1.05]	[-3.59,1.24]	[-0.97,1.03]	[-9.39,3.80]	[-21.42,13.40]
	risk3	-0.78	**1.64***	-0.60	-0.70	-6.08
		[-2.41,0.84]	[-0.23,3.51]	[-5.59,1.39]	[-4.18,2.79]	[-17.91.5.75]
	risk5	-0.56	0.28	-1.22	2.31	3.10
		[-2.86,1.74]	[-0.25,0.81]	[-3.14,0.70]	[-5.17,9.79]	[-11.57,17.77]
Sell Price	# Risky Choices	27.39	-2.24	21.51	38.51	-11.91
		[-15.59,70.37]	[-8.78,4.31]	[-16.69,59.71]	[-39.73,116.75]	[-50.72,26.90]
	risk3	15.91	-5.26	-12.60	89.83	32.08
		[-77.96,109.79]	[-14.57,4.06]	[-94.90,69.70]	[-76.11,255.78]	[-22.19,86.35]
	risk5	47.62	-3.54	27.62	100.70	9.60
		[-38.01,133.25]	[-11.59,4.51]	[-28.40,83.65]	[-90.22,291.62]	[-5.72,24.92]
Sell Volume	# Risky Choices	**0.05*****	0.01	**0.03*****	**0.09*****	0.06
		[0.02,0.08]	[-0.01,0.03]	[0.01,0.05]	[0.03,0.15]	[-0.02,0.14]
	risk3	0.03	0.00	0.03	0.05	0.00
		[-0.02,0.09]	[-0.03,0.04]	[-0.03,0.08]	[-0.05,0.15]	[-0.14,0.14]
	risk5	0.01	0.02	0.00	0.06	0.00
		[-0.03,0.06]	[-0.01,0.05]	[-0.04,0.04]	[-0.03,0.14]	[-0.15,0.14]

OLS estimated coefficients of the risk measures for the respective dependent variable; SE are clustered on the market level; 95% confidence intervals in parentheses; Unit of observation: participant. Additional control variables where 'Age" and 'Gender". The regression results can be found in the appendix C.2.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variables: "Buy(Sell) Price:" Offered buy (sell) prices, in Rappen; "Buy(Sell) Volume:" Number of assets offered to sell.

Independent variables/risk measures: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; 'risk3:" Self-reported answer to the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer to the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)).

"Periods all:" Pooled regression over periods one to fifteen;"Period one:" Regression for the first period; "Periods Before Peak:" Pooled regression over period one to the period with the largest deviation from the market price and the expected value; "Periods After Peak:" Pooled regression over the period with the largest deviation from the market price and the expected value to period fifteen; 'Period fifteen:" Regression for the last period.

Table 3.3: Overview of the OLS coefficients estimate on risk measures (Individual Trading Behavior II)

Dependent Variable	Risk Measure	Periods All	Period One	Periods Before Peak	Periods After Peak	Period Fifteen
Assets	# Risky Choices	0.02	0.02	0.03	0.01	0.00
		[-0.02,0.06]	[-0.01,0.05]	[-0.01,0.07]	[-0.06,0.08]	[-0.07,0.08]
	risk3	**0.07****	-0.01	0.03	**0.16*****	**0.20*****
		[0.00,0.14]	[-0.08,0.06]	[-0.03,0.10]	[0.05,0.26]	[0.08,0.31]
	risk5	0.04	-0.02	0.02	**0.09****	**0.11***
		[-0.02,0.10]	[-0.07,0.03]	[-0.04,0.08]	[0.00,0.18]	[0.00,0.22]
Asset changes	# Risky Choices	0.00	0.01	0.00	-0.1	0.00
		[-0.01,0.00]	[-0.02,0.04]	[0.00,0.01]	[-0.02,0.00]	[-0.03,0.03]
	risk3	**0.01****	-0.02	0.01	**0.02****	**0.06****
		[0.00,0.02]	[-0.09,0.04]	[0.00,0.02]	[0.00,0.05]	[0.00,0.11]
	risk5	**0.01***	-0.02	0.00	0.01	0.04
		[0.00,0.01]	[-0.07,0.02]	[0.00,0.01]	[-0.01,0.03]	[-0.02,0.09]
Participate	# Risky Choices	0.003	0.001	0.002	0.003	0.002
		[-0.002,0.007]	[-0.001,0.002]	[-0.001,0.006]	[-0.005,0.011]	[-0.008,0.011]
	risk3	**0.006***	0.000	0.002	**0.012****	**0.019****
		[-0.001,0.012]	[-0.004,0.005]	[-0.003,0.008]	[0.001,0.024]	[0.003,0.035]
	risk5	**0.005***	0.001	**0.005****	0.003	0.003
		[-0.001,0.010]	[-0.002,0.004]	[0.000,0.011]	[-0.006,0.012]	[-0.010,0.016]

OLS estimated coefficients of the risk measures for the respective dependent variable; SE are clustered on the market level; 95% confidence intervals in parentheses; Unit of observation: participant. Additional control variables where 'Age" and 'Gender". The regression results can be found in the appendix C.2.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variables: "Assets:" Number of assets hold at the end of the period; "Asset changes:" Number of Assets hold at the end of the period less number of assets hold at the beginning of the period; "Participate:" Dummy variable, taking the value 1 if either a buy- or a sell offer was made in the particular period, zero otherwise.
Independent variables/risk measures: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; 'risk3:" Self-reported answer to the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer to the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)).
"Periods all:" Pooled regression over periods one to fifteen;"Period one:" Regression for the first period; "Periods Before Peak:" Pooled regression over period one to the period with the largest deviation from the market price and the expected value; "Periods After Peak:" Pooled regression over the period with the largest deviation from the market price and the expected value to period fifteen; 'Period fifteen:" Regression for the last period.

After the peak of the bubble: The less risk averse the participants in the Holt-Laury Task, the lower is the offered buy price.[46] The effect of a 1.85 Rappen reduction for each unit increase in the # Risky Choices is still not large, considering the average of 141 Rappen (SD: 134) offered as buy prices. Furthermore, the offered number of assets to sell is lower the more risk averse the participants are in the Holt-Laury task.[47] The number of assets hold at the end of the period are higher, the lower the self-reported risk-aversion measures of risk3 and risk5.[48] The more risk-averse participants reported to be in risk3, the less likely they are to make a buy- or sell offer[49] and the lower the number of actual bought or sold assets[50] There are no effects on the offered assets to buy[51] or the offered price to sell an asset.[52]

15th period: The less risk averse the participants in the Holt-Laury Task, the lower is the offered buy price.[53] Given that in this period the average offered buy price is around 43 Rappen (SD: 64), the effect of a reduction by 1.85 Rappen for each unit higher of # Risky Choices is considerable. The number of assets hold at the end of period 15 are higher, the lower the self-reported risk-aversion in risk3 and risk5. Given the average of 2.5 (SD: 3.9) assets hold at the end of period, the effect size of 0.1 or 0.2 more assets hold per unit higher on the risk3 and risk5 measures.[54] The more risk averse participants reported to be in risk3, the less likely participants are to make a buy- or sell-offer[55] and the lower the number of actual bought or sold assets[56] In both cases the effects are considerable. There are no effects on the offered assets to buy[57], the offered price to sell an asset and the number of offered assets to sell.[58]

Result 3.2. ***Risk-Aversion: Market Level***
Markets with, on average, higher risk aversion trade on higher market prices over all periods. This is mainly the result of the periods after the peak of the bubble. Risk-aversion

[46] See table C.23 column (1).
[47] See table C.26 column (1).
[48] See table C.27 column (3,4).
[49] See table C.29 column (3).
[50] See table C.28 column (3).
[51] See table C.25 column (1,3,4).
[52] See table C.24 column (1,3,4).
[53] See table C.30 column (1).
[54] See table C.34 column (3,4).
[55] See table C.36 column (3).
[56] See table C.35 column (3).
[57] See table C.32 column (1,3,4).
[58] See table C.31 columns (1,3,4).

only affects the traded volume of assets in the final period, where markets with on average lower risk aversion have a higher trading volume in period 15.

Table 3.4 summarizes the estimation coefficients obtained from separate OLS regression of the market outcomes and the average of the risk measures at the market level. The discussion of the results will refer to the respective tables in the appendix C.3.

Over all periods the average propensity to take risk in financial matters (market mean of risk3) reduces the market prices.[59] Figure C.4(a) in appendix C.3 suggests, that this is mainly driven by the phases around the bubble peak[60] as the effect size is larger for the phase after the peak of the bubble.[61] If the average at the Holt-Laury task in the market increased by one unite, the market trades after the peak of the bubble is by 23.01 Rappen less. The effect in the last period seems to be smaller then the effects directly after the bubble peak.[62] However, since the market price at the end was on average 49 Rappen (SD: 39), the relative effect size is larger. There are no effects of the average risk measures for the first period.

For trading volume we do not find many effects of the risk measures, beside a small positive and weakly significant effect of the average number of risky choices in the Holt-Laury task for the last period.[63] Furthermore, there are no effects of the average market risk aversion measures on the period the bubble peaks[64] or the largest deviation of the market price from the fundamental value.[65]

[59]See table C.40 column (1).

[60]See table C.40 columns (2,3).

[61]On average the market price is at 331 Rappen (SD: 125) over all periods, at 379 Rappen (SD: 59) before the peak of the bubble and at 197 Rappen (SD: 147) after the peak. The highest (smallest) observed market price was 750 (1) Rappen.

[62]See table C.38 columns (3,5).

[63]See tables C.41 and C.42.

[64]See table C.44columns (1,4).

[65]See table C.44columns (2,5).

Table 3.4: Overview of the coefficients of the OLS regressions on the market outcome variables

Dependent Variable	Risk Measure	Periods All	Period One	Periods Before Peak	Periods After Peak	Period Fifteen
Market Price	# Risky Choices	-8.13	4.58	-0.44	**-23.01***	**-12.01***
		[-18.26,2.00]	[-3.47,12.62]	[-6.37,5.50]	[-46.07,0.05]	[-24.36,0.34]
	risk3	**-20.67***	10.72	**-15.25****	**-45.50***	-3.51
		[-43.19,1.85]	[-6.97,28.41]	[-28.98,-1.53]	[-92.25,1.25]	[-31.44,24.41]
	risk5	**-15.91***	4.34	-9.10	-27.68	-0.66
		[-33.28,1.47]	[-9.79,18.47]	[-20.15,1.94]	[-69.26,13.90]	[-22.61,21.29]
Trading Volume	# Risky Choices	0.04	0.22	0.06	0.08	**1.43***
		[-0.21,0.30]	[-0.70,1.15]	[-0.23,0.34]	[-0.49,0.65]	[-0.00,2.86]
	risk3	0.19	0.13	0.18	0.35	-1.03
		[-0.36,0.75]	[-1.91,2.18]	[-0.47,0.84]	[-0.81,1.50]	[-4.33,2.28]
	risk5	-0.07	-0.75	-0.19	0.31	-0.74
		[-0.51,0.37]	[-2.34,0.84]	[-0.65,0.27]	[-0.72,1.33]	[-3.35,1.86]

Coefficients are obtained by OLS regression of the risk measure for the respective dependent variable; 95% confidence intervals in squared parentheses; Unit of observation: Markets. The regression results can be found in the appendix C.3.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variables: "Market Price:" Price at the end of the respective period at which the assets were traded, in Rappen; "Trading Volume:" Number of assets that were traded in this period;

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)); "# OCrel:" relative over-confidence measure.

"Periods all:" Pooled regression over periods one to fifteen;"Period one:" Regression for the first period; "Periods Before Peak:" Pooled regression over period one to the period with the largest deviation from the market price and the expected value; "Periods After Peak:" Pooled regression over the period with the largest deviation from the market price and the expected value to period fifteen; 'Period fifteen:" Regression for the last period.

3.5.2 Realtive Over-Confidence

Result 3.3. ***Relative over-confidence: Individual Trading Behaviour***
There is only one (weakly) significant effects of relative over-confidence on the individual trading behaviour: After the peak of the bubble participants with a higher relative over-confidence tend to offer a lower number of assets to sell. There are no other effects on the other parameters of individual trading or the final earnings from the asset market.

Table 3.5 summarizes the coefficients obtained from OLS regressions of variables of individual trading behaviour on relative over-confidence, age and gender. The discussion of the results will refer to the respective regression tables in the appendix C.2.

There is a weakly significant negative effect of a higher relative over-confidence on the offered volume to sell the asset after the peak of the bubble.[66] In the periods after the peak of the bubble the participants offered on average 2.9 assets so sell (SD: 2.63), thus the effect size of a reduction in the numbers of assets offered to sell by 0.18 if the relative over-confidence increases by one unit, is not small but not huge either. Otherwise, there are no significant and robust effects on the individual level for the relative over-confidence on either of the outcome variables or in either of the phases of the bubble formation.[67]

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[66]See table C.26 column (2).

[67]See tables C.2 to C.37 column (2).

Table 3.5: Overview of the coefficients of the OLS regressions of the individual trading behavior variables on relative over-confidence

Dependent Variable	Periods All	Period One	Periods Before Peak	Periods After Peak	Period Fifteen
Buy Price	3.14	-3.25	2.68	5.57	-0.27
	[-1.39,7.66]	[-11.50,5.00]	[-1.94,7.30]	[-2.16,13.30]	[-5.51,4.61]
Buy Volume	-1.39	1.10	-2.38	2.46	15.24
	[-4.74,1.95]	[-0.53,2.74]	[-5.65,0.88]	[-9.28,14.19]	[-19.05,49.52]
Sell Price	19.00	-2.62	-24.58	143.72	-8.09
	[-112.11,150.11]	[-15.74,10.49]	[-116.93,67.77]	[-136.38,423.82]	[-32.38,16.21]
Sell Volume	-0.06	-0.03	-0.03	**-0.18***	0.01
	[-0.16,0.04]	[-0.09,0.02]	[-0.10,0.05]	[-0.40,0.03]	[-0.25,0.27]
Assets	0.00	0.03	0.01	-0.02	0.08
	[-0.11,0.11]	[-0.09,0.15]	[-0.10,0.12]	[-0.19,0.14]	[-0.11,0.26]
Asset changes	0.01	0.06	0.00	0.02	0.04
	[-0.01,0.02]	[-0.05,0.18]	[-0.02,0.02]	[-0.02,0.07]	[-0.01,0.18]
Participate	0.005	-0.001	0.003	0.010	0.020
	[-0.005,0.015]	[-0.005,0.004]	[-0.006,0.012]	[-0.008,0.028]	[-0.004,0.043]

OLS estimated coefficients of the risk measures for the respective dependent variable; SE are clustered on the market level; 95% confidence intervals in parentheses; Unit of observation: participant. Additional control variables where ‘Age” and ‘Gender”. The regression results can be found in the appendix C.2.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variables: “Buy(Sell) Price:” Offered buy (sell) prices, in Rappen; “Buy(Sell) Volume:” Number of assets offered to sell; “Assets:” Number of assets hold at the end of the period; “Asset changes:” Number of Assets hold at the end of the period less number of assets hold at the beginning of the period; “Participate:” Dummy variable, taking the value 1 if either a buy- or a sell offer was made in the particular period, zero otherwise.
Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)).
“Periods all:” Pooled regression over periods one to fifteen;“Period one:” Regression for the first period; “Periods Before Peak:” Pooled regression over period one to the period with the largest deviation from the market price and the expected value; “Periods After Peak:” Pooled regression over the period with the largest deviation from the market price and the expected value to period fifteen; ‘Period fifteen:” Regression for the last period.

Result 3.4. ***Over-confidence: Market Outcome***
Markets with, on average, higher relative over-confidence trade on higher market prices and have a larger number of assets traded over all periods. The overall higher market prices are mainly driven by the periods before the peak of the bubble. Markets with, on average, higher relative over-confidence tend to have a lower market price in the first period. The higher trading volume in markets with higher relative over-confidence is mostly the result of the periods after the peak of the bubble and, in particular of period 15. The average relative over-confidence in a market does not influence the timing of the bubble burst and the largest deviation of the market price from the fundamental value.

Table 3.4 summarizes the estimation coefficients of OLS regressions at the market level of market outcome variables on relative over-confidence. The discussion of the results will refer to the respective regression tables in the appendix C.3.

Table 3.6: Overview of the estimation coefficients of the regressions on the dependet variables (Market Outcome)

Dependent Variable	Periods All	Period One	Periods Before Peak	Periods After Peak	Period Fifteen
Market Price	**29.19****	**-20.11****	**28.91*****	38.69	-21.25
	[5.19,53.19]	[-38.49,-1.72]	[15.12,42.70]	[-16.40,93.79]	[-50.44,7.95]
Trading Volume	**0.59***	0.85	0.35	**1.44****	**3.18***
	[-0.01,1.19]	[-1.34,3.05]	[-0.33,1.03]	[0.10,2.78]	[-0.27,6.63]

OLS regression coefficients of market outcome variables on relative over-confidence; 95% confidence intervals in squared parentheses; Unit of observation: Markets. The regression results can be found in the appendix C.3.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Dependent variables: "Market Price:" Price at the end of the respective period at which the assets were traded, in Rappen; "Trading Volume:" Number of assets that were traded in this period;
Independent variables: "# OCrel:" relative over-confidence measure.
"Periods all:" Pooled regression over periods one to fifteen;"Period one:" Regression for the first period; "Periods Before Peak:" Pooled regression over period one to the period with the largest deviation from the market price and the expected value; "Periods After Peak:" Pooled regression over the period with the largest deviation from the market price and the expected value to period fifteen; 'Period fifteen:" Regression for the last period.

The market price is higher in markets with on average higher relative over-confidence.[68] This is mainly driven by the periods before the peak of the bubble[69], while there is no effect of the average relative over-confidence on the market price for periods after the burst of the bubble.[70] The market prices is lower in the first period for markets with, on average, higher over-confident participants.[71] There is no such effect for the last period.[72]

[68]See table C.45 column (1). Confirming the visual impression of figure C.5(a).

[69]See table C.45 column (2).

[70]See table C.45 column (3).

[71]See table C.45 column (4).

[72]See table C.45 column (5).

There are no effects of the average relative over-confidence on the period of the bubble peak[73] or the largest deviation of the market price from the fundamental value.[74]

The trading volume over all periods tends to be higher if the average relative over-confidence in the market is higher[75], which is mostly the result of the periods after the bubble peak[76] and, in particular the final period.[77] There are no significant effects of relative over-confidence on trading volume for the first period and the periods before the peak of the bubble.[78]

3.6 Discussion and Conclusion

The purpose of this manuscript is to re-examine the role of risk-attitudes and over-confidence in experimental asset markets by using the results of 40 experimental asset markets with 16 participants in each market. Risk attitudes are elicited by giving participants 20 choices between a certain outcome and a risky lottery (Holt and Laury, 2002). Answers to self-reported questions of the final exit questionnaire are also used to measure the risk attitude in a more broader every-day sense. Relative over-confidence is measured by letting people answer the Raven's-Matrix IQ-Test and asking them in which quintile, among all participant, with respect to correct answers they expect to be with their answers. The deviation between the expected quintile and the real quintile yields the degree of relative over-confidence.

Risk-aversion: On the individual level no risk-aversion measure correlates with the final pay-off from the experiment, the offered number of assets to buy or offered prices to sell. Nevertheless, the offered buy price declines over all periods when participants are more risk averse in career matters. The magnitude of the latter effect is small and the coefficient estimates are only weakly significant. However, if risk aversion is measured by

[73]See table C.47column (1).
[74]See table C.47column (2).
[75]See table C.46 column (1). Contrary to what one might guess from figure C.5(b):
[76]See table C.46 column (3).
[77]See table C.46 column (5).
[78]See table C.46 columns (2,4).

the number of risky lottery choices (Holt-Laury Task) more risk averse participants tend to offer lower buy prices once the bubble bursts; this effect is weakly significant. This finding contradicts Ang et al. (2010) and Breaban and Noussair (2015), who also used a Holt-Laury-task and find that less risk-averse participants trade on higher prices.

In line with hypothesis 3.1 and the findings of Fellner and Maciejovsky (2007) and contrary to Breaban and Noussair (2015), during all 15 periods, more risk-averse participants tend to offer less assets to sell, hold fewer assets, make less often bid- and sell-offers and are involved in fewer successful trades. In the majority of the cases the self-reported risk-aversion with respect to financial decisions correlates with the outcome variables. While these effects are small in size for the whole market, the effects become stronger after the peak of the bubble and particularly in the final period one can speak of a considerable effect of the risk-measures.

On the market level, there is no correlation between the risk-measures and the traded volume for all 15 periods; which supports hypothesis 3.2. However, the higher the average number of risky-choices in the Holt-Laury-task, the higher is the trading volume in the final period. The market price tends to be lower if average risk-aversion is lower in the market. This contradicts the result of Eckel and Füllbrunn (2015) and confirms both: The finding of Breaban and Noussair (2015) and hypothesis 3.3, that the market price is closer to the fundamental value if traders in the market are less risk-averse, on average.[79] Again this effect is mainly driven by the periods after the peak of the bubble.

There are three general observations: (1) For the first period, the only weakly significant effect we find is that participant who have a low self-reported risk-aversion in financial matters (risk3), tend to offer more assets to buy. Otherwise, there are no effects of the risk-measures on trading behaviour. This contradicts the view that due to risk-averse participants, the market price starts below the expected value in this kind of experimental asset markets. (2) Most of the effects over all periods are small, (weakly) significant and mainly driven by the final period. In fact, the decision in the final pe-

[79]Since the fundamental value is declining in the experimental asset market, from the theory discussed in section 3.3 one would expect a lower market price in markets with less risk-averse participants.

riod differs from decisions in the previous periods, because over the whole asset market uncertainty arises from two sources: First, due to the random dividend draws (nature risk). Second, by intentional sources such as the action of others or the opponents risk (Bossaerts, 2009). Both risk components do not necessarily have to be correlated with each other. Uncertainty stemming from nature is processed differently in the brain, when compared to uncertainty due to intentional agents, which is perceived more like a situation of ambiguity (Bossaerts, 2009). Thus, preferences over uncertainty due to nature or intentional sources can be different. For this reason, the main difference of the final period from preceding periods, is the absence of the re-selling motivation. In period 15 the value of the asset is only determined by the last random dividend draw (nature risk). The uncertainty in the Holt-Laury task stems only from a lottery (nature risk). Hence, this might help to explain, why one finds mainly correlations between individual trading behaviour variables and risk-measures in the final period or towards the end of the experiment.[80]
(3) Finally, since the self-reported questions allow participants to broader interpret the meaning of risk-attitudes, they also show more often correlation with individual trading outcomes over the whole asset market.

Relative Over-Confidence: On the individual level, there is no correlation between the relative over-confidence measure and the earnings from the asset market. This contradicts the finding of Smith (2012), that more over-confident traders perform better. The only (weakly) significant effect is: Relative over-confident participants offer more assets to sell after the peak of the bubble. The weak significance of the effect raises the question of whether there are correlations among relative over-confidence and individual trading behaviours at all; albeit this finding is consistent with Smith (2012) who finds that over-confidence does not affect the the number of trades made.

[80]The findings of Porter and Smith (1995) underline this interpretation. They introduced in an experimental asset market certain per-period dividend and thus eliminated (nature) risk from the dividend. This change did not alter the bubble in markets with inexperienced traders. Indicating, that even in the absence of risky fundamentals, there are participants willing to pay a price above the certain dividend outcome; either by having problems to understand the link between price of an asset and expected value or by ambiguity about the other traders intention.

Markets with, on average, higher relative over-confident participants, tend to have a higher trading volume, supporting hypothesis 3.4. The trading volume is particularly large once the bubble burst. Furthermore, markets with an higher average of relative over-confidence trade on higher market prices, in particular around the peak of the bubble. This results in larger bubbles and is in line with the findings of Kirchler and Maciejovsky (2002), Michailova (2011) and Oechssler et al. (2011). It contradicts Smith (2012) and hypothesis 3.5, that over-confidence does not affect the price of the price of the asset market.

In sum, beside hypothesis 3.5, all other hypotheses derived from a standard noisy rational expectation asset pricing model (Hellwig, 1980), are supported. In general, the effects are small and mostly weakly significant on the individual level. Moreover, they are not pay-off relevant. Thus further research might consider: (1) Since the self-reported questions on risk-attitude are more often correlated with trading behaviour and market outcomes, one should reconsider measuring risk-aversion with the choice of lotteries. If the Holt-Laury task is used to measure risk preferences, one tests only for preferences on the first moment of a distribution. In fact, participants might have preferences over higher moments as well (,e.g. skewness and kurtiosis) (Bossaerts, 2009). Recent work, e.g. Andersen et al. (2014); Ebert (2015) and Harrison et al. (2015), developed risk-measures based on asking for preferences over the whole distribution. (2) In light of this studies result, one might want to disentangle the effect of risk preferences over uncertainty from nature and intentional sources in decision making. This raises the question of what serves as an appropriate measure to elicit preferences over uncertainty from intentional sources. (3) The existence of two different sources of risk which shape risk preferences over uncertainty, calls for a re-consideration of current theoretical models. New theoretical models should provide predictions on how preferences about distributions of outcomes and risk stemming from intentional sources affects financial decision making. The application of prospect theory on financial decision making seems a promising avenue (Ebert and Strack, 2015, 2016) for nature risk. (4) Finally, the fact that over-confidence is barely correlated with individual trading behaviour but affects market outcomes, casts doubt on current measurements of over-confidence. Furthermore, on a theory level, how the interaction of over-confident participants, that do not show much difference in behaviour at the individual level, leads to difference in outcomes on the market level (i.e., if the market average of over-confidence increases the market price increases, too).

Part III

Appendices

A Appendix: Chapter 1

A.1 On Mutual Information

Mutual information is defined as $I\left(y,x\right) = \frac{1}{2}\log_2\left(\frac{\sigma_y^2}{\sigma_{y|x}^2}\right)$, that is the information contained in a random variable $x \sim N(\mu_x, \sigma_x^2)$ about another random variable $y \sim N(\mu_y, \sigma_y^2)$ with $\sigma_{y|x}^2$ as the conditional variance of y once x has been observed. Since the concept is symmetric and based on entropy, mutual information answers the question by how much the entropy is reduced of one variable by knowing the other. Thus intuitively mutual information quantifies the information needed to describe y if x is already known (Veldkamp, 2011, p.19f).

The following example from Wiederholt et al. (2010) p. 3 should help to grasp the idea of rational inattention. Think of x as the variable of interest to the decision maker. Since the decision maker has limited attention resources, the perception of x will be noisy. Thus the attention choice to the variable x can be modelled as receiving a signal $y = x + \epsilon$ where the ϵ is the noise, due to the limited attention of the decision maker and independent of x and normally distributed with mean zero and σ_ϵ^2. Limited attention is modelled by a bound on the information flow:

$$I\left(y,x\right) = \frac{1}{2}\log_2\left(\frac{\sigma_y^2}{\sigma_{y|x}^2}\right) \leq \kappa \tag{A.1}$$

With $\sigma_{y|x}^2 = \sigma_x^2 - \frac{\sigma_x^4}{\sigma_x^2 + \sigma_\epsilon^2}$ this is equivalent to

$$\frac{\sigma_x^2}{\sigma_\epsilon^2} \leq 2^{2\kappa} - 1 \tag{A.2}$$

In this example, limited attention leads a bound on the variance reduction, which implies a bound on the signal-to-noise ratio in the signal y concerning x.

With the correlation coefficient $R_{xy} = \frac{\sigma_x^2}{\sqrt{\sigma_x^2+\sigma_\epsilon^2}}$ of the random variables x and y one can rewrite the mutual information by $I(y,x) = \frac{1}{2}\log_2 \frac{1}{1-R_{xy}^2}$.

A.2 Single Asset Price

This section solves the optimal asset allocation described by 1.7 to 1.7 under the assumption of mean-variance utility. First, one replaces c_t and c_{t+1} in the objective function by its respective expressions from the side constraints. Since there is no uncertainty in the first period, the variance will be zero in this case.

$$\arg\max_{q_t} e - q_t p_t + \beta q_t \mathbb{E}\left[\tilde{d}_{t+1}|\tilde{d}_t^r(\tau_r)\right] - \frac{\rho}{2} q_t^2 Var(\tilde{d}_{t+1}|\tilde{d}_t^r(\tau_r)) \tag{A.3}$$

The conditional expectation can be also rewritten by applying the projection theorem:[1]

$$\begin{aligned}
&\arg\max_{q_t} e - q_t p_t + \beta \left(q_t \left(\mu + \frac{Cov(\tilde{d}_t^s, \tilde{d}_t^r)}{Var(\tilde{d}_t^r)} \left(\tilde{d}_t^r - \mu^*\right)\right) - \frac{\rho}{2} q_{t+1}^2 \left(Var\left(\tilde{d}_t^s\right) - \frac{Cov^2(\tilde{d}_t^s, \tilde{d}_t^r)}{Var(\tilde{d}_t^r)} \right)\right) \\
&\arg\max_{q_t} e - q_t p_t + \beta \left(q_t \left(\frac{\frac{1}{\tau_r^2}}{\sigma_s^2 + \frac{1}{\tau_r^2}} \mu + \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}} \left(\tilde{d}_{t+1}^* + \frac{\epsilon_t^s}{\tau_s} + \frac{\epsilon_t^r}{\tau_r} \right)\right) - \frac{\rho}{2} q_t^2 \left(\sigma_s^2 - \frac{\sigma_s^4}{\sigma_s^2 + \frac{1}{\tau_r^2}} \right)\right)
\end{aligned} \tag{A.4}$$

using the definition of correlation $R = \frac{\sigma_s}{\sqrt{\sigma_s^2 + \frac{1}{\tau_r^2}}}$ one can simplify the expression $\sigma_s^2 - \frac{\sigma_s^4}{\sigma_s^2+\frac{1}{\tau_r^2}} = \sigma_s^2\left(1-R^2\right)$. Taking the first order condition of A.4 and solve for the optimal quantity q_t^{opt} of asset hold:

$$q_t^{opt} = \frac{1}{\rho\sigma_s^2\left(1-R^2\right)} \left(\frac{\frac{1}{\tau_r^2}}{\sigma_s^2 + \frac{1}{\tau_r^2}} \mu^* + \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}} \left(\tilde{d}_{t+1}^* \frac{\epsilon_t^s}{\tau_s} + \frac{\epsilon_t^r}{\tau_r} \right) - \frac{p_t}{\beta} \right) \tag{A.5}$$

[1] Consider two normal distributed variables $x_i \sim N(\mu_i, \sigma_i^2)$ and $x_j \sim N(\mu_j, \sigma_j^2)$, then $(x_j \,\middle|\, x_i = a) \sim N(\hat{\mu}, \hat{\sigma}^2)$ with $\hat{\mu} = \mu_j + \frac{Cov(x_j,x_i)}{\sigma_i^2}(a-\mu_i)$ and $\hat{\sigma}^2 = \sigma_j^2 - \frac{(Cov(x_j,x_i))^2}{\sigma_i^2}$ (Vives, 2010) section 10.2.1.

Since there is only one investor in this economy, in equilibrium she holds all assets, thus without loss of generality one can set $q_t^{opt} = 1$ and derive from A.5 the equilibrium price:

$$p_t^{eq} = \beta \left[\frac{\frac{1}{\tau_r^2}}{\sigma_s^2 + \frac{1}{\tau_r^2}} \mu + \frac{\sigma_s^2}{\sigma_s^2 + \frac{1}{\tau_r^2}} \left(\tilde{d}_{t+1}^* + \frac{\epsilon_{t+1}^s}{\tau_s} + \frac{\epsilon_t^r}{\tau_r} \right) - \rho \sigma_s^2 \left(1 - R^2 \right) \right] \tag{A.6}$$

A.3 Derivation of Σ_1

Following Vives (2010) p. 121 one can interpret the equilibrium asset price as an estimate of the dividend. When the price would be fully revealing, there would be no uncertainty left, $Var\left(\tilde{d}|p\right) = 0$, and if the price is pure noise, there would be no reduction in uncertainty, $Var\left(\tilde{d}|p\right) = Var\left(\tilde{d}\right)$. In the following I will derive $Var\left(\tilde{d}|p\right) = \Sigma_1$ for the single asset case. Before that one has to find the expected variance of the asset price in equilibrium 1.12:

$$\begin{aligned} Var(p_t^{eq}) &= \mathbb{E}\left[(p_t^{eq} - \mathbb{E}(p_t^{eq}))^2 \right] && \text{(A.7)} \\ &= \frac{\sigma_s^4}{\left(\sigma_s^2 + \frac{1}{\tau_r^2}\right)^2} \left(\sigma^{*2} + \frac{1}{\tau_s^2} + \frac{1}{\tau_r^2} \right) && \text{(A.8)} \\ &= \frac{\sigma_s^4}{\sigma_s^2 + \frac{1}{\tau_r^2}}, && \text{(A.9)} \end{aligned}$$

by making use of $\sigma_s^2 = \sigma^{*2} + \frac{1}{\tau_s^2}$ for the last step and the co-variance between the price and the dividend:

$$Cov(\tilde{d}, p) = \frac{\sigma_s^4}{\left(\sigma_s^2 + \frac{1}{\tau_r^2}\right)^2} \sigma^{*2}. \tag{A.10}$$

With this at hand the conditional variance is Σ_1 can be calculated by using the projection theorem for conditional variance:[2]

$$\Sigma_1 = \sigma^{*2} - \frac{Cov(\tilde{d}, p)^2}{Var(p)} \tag{A.11}$$

$$= \sigma^{*2} - \frac{\sigma_s^4}{\left(\sigma_s^2 + \frac{1}{\tau_r^2}\right)^3}\sigma^{*4} \tag{A.12}$$

Taking the partial derivative of Σ_1 with respect to τ_r^2:

$$\frac{\partial \Sigma_1}{\partial \tau_r^2} = -3\frac{\sigma_s^4}{\left(\sigma_s^2 + \frac{1}{\tau_r^2}\right)^4}\sigma^{*4}\frac{1}{\tau_r^4} < 0 \tag{A.13}$$

A.4 Derivation of the Value-function in the Multi-Asset case

This is the proof for Lemma 1.1:

Simplifying the investment problem stated in equation 1.14- 1.16

$$\arg\max_{\mathbf{q}_t} e - \mathbf{q}_t^{'}\mathbf{p}_t + \beta\left(\mathbb{E}\left[\mathbf{q}_t^{'}\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right] - \frac{\rho}{2}Var\left(\mathbf{q}_t^{'}\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right)\right) \tag{A.14}$$

This can be also expressed by applying the projection theorem:

$$\arg\max_{\mathbf{q}_t} e - \mathbf{q}_t^{'}\mathbf{p}_t + \beta\left(\sum_{i=1}^{I} q_{i,t}\left(\mu_i + \frac{Cov(\tilde{d}_{i,t+1}^s, \tilde{d}_{i,t+1}^r)}{Var(\tilde{d}_{i,t+1}^r)}\left(\tilde{d}_{i,t+1}^r - \mu_i\right)\right) - \frac{\rho}{2}\sum_{i=1}^{I} q_{i,t}^2\left(Var\left(\tilde{d}_{i,t+1}^s\right) - \frac{Cov^2(\tilde{d}_{i,t+1}^s, \tilde{d}_{i,t+1}^r)}{Var(\tilde{d}_{i,t+1}^r)}\right)\right) \tag{A.15}$$

$$\arg\max_{\mathbf{q}_t} e - \mathbf{q}_t^{'}\mathbf{p}_t + \beta\left(\sum_{i=1}^{I} q_{i,t}\left(\frac{\frac{1}{\tau_{i,r}^2}}{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}\mu_i + \frac{\sigma_{i,s}^2}{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}\left(\sigma^* + \frac{\epsilon_{i,t+1}^s}{\tau_{i,s}} + \frac{\epsilon_{i,t+1}^r}{\tau_{i,r}}\right)\right) - \frac{\rho}{2}\sum_{i=1}^{I} q_{i,t}^2\left(\sigma_{i,s}^2 - \frac{\sigma_{i,s}^4}{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}\right)\right) \tag{A.16}$$

using the definition of correlation $R_i = \frac{\sigma_{i,s}}{\sqrt{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}}$ one can simplify the expression $\sigma_{i,s}^2 - \frac{\sigma_{i,s}^4}{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}} = \sigma_{i,s}^2\left(1 - R_i^2\right)$. Taking the first order condition with respect to $q_{i,t}^{opt}$, the optimal

[2]See Vives (2010) chapter 10 on details for that.

quantity $q_{i,t}^{opt}$ hold of asset $i \in I$ is given by:

$$q_{i,t}^{opt} = \frac{1}{\rho\sigma_{i,s}^2\left(1-R_i^2\right)}\left(\frac{\frac{1}{\tau_{i,r}^2}}{\sigma_{i,s}^2+\frac{1}{\tau_{i,r}^2}}\mu_i + \frac{\sigma_{i,s}^2}{\sigma_{i,s}^2+\frac{1}{\tau_{i,r}^2}}\left(\sigma^* + \frac{\epsilon_{i,t+1}^s}{\tau_{i,s}} + \frac{\epsilon_{i,t+1}^r}{\tau_{i,r}}\right) - \frac{p_{i,t}}{\beta}\right) \quad \text{(A.17)}$$

Since there is only one reciever in this economy, in equilibrium she holds all shares of the assets, thus without loss of generality one can set $q_{i,t}^{opt} = 1$ and derive from A.17 the equilibrium price $p_{i,t}^{eq}$:

$$p_{i,t}^{eq} = \beta\left[\frac{\frac{1}{\tau_{i,r}^2}}{\sigma_{i,s}^2+\frac{1}{\tau_{i,r}^2}}\mu_i + \frac{\sigma_{i,s}^2}{\sigma_{i,s}^2+\frac{1}{\tau_{i,r}^2}}\left(\sigma^* + \frac{\epsilon_{i,t+1}^s}{\tau_{i,s}} + \frac{\epsilon_{i,t+1}^r}{\tau_{i,r}}\right) - \rho\sigma_{i,s}^2\left(1-R_i^2\right)\right] \quad \text{(A.18)}$$

Note that the risk-premium $\rho\sigma_{i,s}^2\left(1-R_i^2\right)$ varies with either (1) a change in the precision $\tau_{i,r}^2$ with which the reciever r processes the information or with (2) the precision of the information send by the sender, which might be due to a lower error in the observation $\frac{\epsilon_{i,t+1}^s}{\tau_{i,s}^2}$ or due to a lower variance σ_i^{*2} in the underlying dividend generating process of asset $i \in I$. In each of the above mentioned cases, the risk-premium changes in the opposed direction as the change in the underlying factor,(i.e. if $\tau_{i,r}^2$ increases the risk-premium decreases by $-\frac{\rho}{\left(\tau_{i,r}^2+\sigma_{i,s}^{-2}\right)^2}$).

Applying the equilibrium condition, $q_{i,t}^{opt} = 1\,\forall\, i \in I$ to A.16, the value function $V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r))$ becomes:

$$V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)) = e - \mathbf{p}_t + \beta\left(\mathbb{E}\left[\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right] - \frac{\rho}{2}Var\left(\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right)\right) \quad \text{(A.19)}$$

Note that in expectation for the investor $\mathbf{p}_t$ and $mathbbE\left[\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right]$ are invariant to changes in τ_r. Thus she maximizes $V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r))$ by minimizing the variance $Var\left(\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right)$

$$\begin{aligned} max_{\boldsymbol{\tau}_r} V(\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)) \quad &\leftrightarrow min_{\boldsymbol{\tau}_r} Var\left(\tilde{\mathbf{d}}_{t+1}\middle|\tilde{\mathbf{d}}^r(\boldsymbol{\tau}_r)\right) && \text{(A.20)}\\ &\leftrightarrow min_{\boldsymbol{\tau}_r} \sum_{i=1}^{I}\left(\sigma_{i,s}^2 - \frac{\sigma_{i,s}^4}{\sigma_{i,s}^2+\frac{1}{\tau_{i,r}^2}}\right) && \text{(A.21)}\\ &\leftrightarrow \min_{\{R_i^2\}_{i=1}^{I}} \sum_{i=1}^{I}\sigma_{i,s}^2\left(1-R_i^2\right) && \text{(A.22)}\end{aligned}$$

$R_i = \frac{\sigma_{i,s}}{\sqrt{\sigma^2_{i,s}+\frac{1}{\tau^2_{i,r}}}}$ is the correlation between the information distributed by sender s on asset i and information extracted by the investor r. C.p. an increase in R_i goes along with an increase in $\tau^2_{i,r}$ and vice versa.

A.5 Derivation of κ_j^{opt}

Applying Lemma 1.1 the attention allocation problem stated in 1.18 and 1.19 can now be written in terms of R_i:

$$\min_{\mathbf{R}} \sum_{i=1}^{I} \sigma^2_{i,s} \left(1 - R_i^2\right) \tag{A.23}$$

subject to

$$\sum_{i=1}^{I} \mathbb{I}(R_i, v_i) \leq \kappa \tag{A.24}$$

The partial derivative of the attention effort constraint with respect to R_i^2:

$$\frac{\partial \sum_{i=1}^{I} \mathbb{I}(R_i, v_i)}{\partial R_i^2} = \frac{1}{2v_i ln2} \frac{1}{(1 - R_i^2)^2} \tag{A.25}$$

Plugging equation A.25 into the equilibrium condition 1.21 one receives equation 1.22:

$$\left(\frac{1 - R_j^2}{1 - R_i^2}\right)^2 \frac{v_j}{v_i} = \frac{\sigma^2_{i,s}}{\sigma^2_{j,s}} \tag{1.22}$$

Solving this for R_j yields:[3]

$$\frac{1 - R_j^2}{1 - R_i^2} = \frac{\sigma_{i,s}}{\sigma_{j,s}} \sqrt{\frac{v_i}{v_j}} \tag{A.26}$$

$$R_j = \sqrt{1 - \frac{\sigma_{i,s}}{\sigma_{j,s}} \sqrt{\frac{v_i}{v_j}} (1 - R_i^2)} \tag{A.27}$$

[3]Since $\frac{1-R_j^2}{1-R_i^2} \geq 0$ only the positive solution of the square-root is relevant.

A.27 holds for all assets $j \neq i$ and $\{i,j\} \in I$. Therefore plug A.27 back into the binding attention effort constraint A.24 one receives an expression for R_i:[4]

$$\begin{aligned}
\mathbb{I}\left(\mathbf{R},\mathbf{v}\right) = \sum_{i=0}^{I} \frac{1}{2v_i} log_2\left(\frac{1}{1-R_i^2}\right) &= \kappa && \text{(A.28)}\\
\sum_{i=0}^{I} \frac{1}{v_i} ln\left(\frac{1}{1-R_i^2}\right) &= 2\kappa ln2 && \text{(A.29)}\\
\prod_{i=0}^{I} \left(\frac{1}{1-R_i^2}\right)^{\frac{1}{v_i}} &= 4^{\kappa} && \text{(A.30)}\\
\left(\frac{1}{1-R_i^2}\right)^{\frac{1}{v_i}} \prod_{\substack{j\neq i\\ j=0}}^{I} \left(\frac{1}{1-R_j^2}\right)^{\frac{1}{v_j}} &= && \text{(A.31)}\\
\left(\frac{1}{1-R_i^2}\right)^{\frac{1}{v_i}} \prod_{\substack{j\neq i\\ j=0}}^{I} \left(\frac{1}{\frac{\sigma_{i,s}}{\sigma_{j,s}}\sqrt{\frac{v_i}{v_j}}\left(1-R_i^2\right)}\right)^{\frac{1}{v_j}} &= && \text{(A.32)}\\
\left(\frac{1}{1-R_i^2}\right)^{\frac{1}{v_i}+\sum_{j\neq i, j=0}^{I}\frac{1}{v_j}} \prod_{\substack{j\neq i\\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}} &= && \text{(A.33)}\\
\left(1-R_i^2\right)^{\frac{1}{v_i}+\sum_{j\neq i, j=0}^{I}\frac{1}{v_j}} &= 4^{-\kappa} \prod_{\substack{j\neq i\\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}} && \text{(A.34)}\\
R_i^2 &= 1-\left[4^{-\kappa} \prod_{\substack{j\neq i\\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{j\neq i, j=0}^{I}\frac{1}{v_j}}} && \text{(A.35)}
\end{aligned}$$

Plugging A.35 back into $\kappa_i = \frac{1}{2v_i} log_2\left(\frac{1}{1-R_i^2}\right)$ one receives the optimal attention allo-

[4] The first four steps are just a conversion of the attention effort constraint.

cation:

$$\kappa_i^{opt} = \frac{1}{2v_i} log_2 \left(\frac{1}{\left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}}} \right) \tag{A.36}$$

$$= \frac{1}{2v_i ln2} \frac{1}{\frac{1}{v_i} + \sum_{\substack{j\neq i \\ j=0}}^{I} \frac{1}{v_j}} ln \left(4^{\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\sqrt{\frac{v_i}{v_j}}\right)^{\frac{1}{v_j}} \right) \tag{A.37}$$

$$= \frac{1}{ln4} \frac{1}{1 + \sum_{\substack{j\neq i \\ j=0}}^{I} \frac{v_i}{v_j}} \left(\kappa ln4 + \sum_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{1}{v_j} ln \frac{\sigma_{i,s}}{\sigma_{j,s}} + \frac{1}{2v_j} ln \frac{v_i}{v_j} \right) \right) \tag{A.38}$$

With $R_i = \frac{\sigma_{i,s}}{\sqrt{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}}}$ one can also derive the optimal precision $\tau_{i,r}^2$:

$$R_i = \frac{\sigma_{i,s}^2}{\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2}} = 1 - \left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}} \tag{A.39}$$

$$\sigma_{i,s}^2 + \frac{1}{\tau_{i,r}^2} = \frac{\sigma_{i,s}^2}{1 - \left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}}} \tag{A.40}$$

$$\frac{1}{\tau_{i,r}^2} = \sigma_{i,s}^2 \left(\frac{1}{1 - \left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}}} - 1 \right) \tag{A.41}$$

$$= \sigma_{i,s}^2 \left(\frac{\left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}}}{1 - \left[4^{-\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}}} \right) \tag{A.42}$$

$$\tau_{i,r}^{2opt} = \frac{1}{\sigma_{i,s}^2} \left(\left[4^{\kappa} \prod_{\substack{j\neq i \\ j=0}}^{I} \left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\sqrt{\frac{v_i}{v_j}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i \\ j=0}}^{I}\frac{1}{v_j}}} - 1 \right) \tag{A.43}$$

A.6 Attention maximizing visibility v_i^*

$$\begin{aligned}
\frac{\partial \kappa_i^{opt}}{\partial v_i} &= \frac{1}{ln4}\frac{-\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}}{\left(1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}\right)^2}\left(\kappa ln4+\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{1}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}+\frac{1}{2v_j}ln\frac{v_i}{v_j}\right)\right) && \text{(A.44)}\\
&\quad+\frac{1}{ln4}\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\left(\frac{1}{v_i}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{2v_j}\right)\\
&= \frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\left(\frac{1}{ln4}\frac{1}{v_i}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{2v_j}-\kappa_i^{opt}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}\right) && \text{(A.45)}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \kappa_i^{opt}}{\partial v_i}=0 \quad\Leftrightarrow\quad \frac{1}{ln4}\frac{1}{v_i^*}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{2v_j} &= \kappa_i^{opt}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}\\
\frac{1}{2ln4}\frac{1}{v_i^*} &= \kappa_i^{opt}\\
&= \frac{1}{ln4}\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i^*}{v_j}}\left(\kappa ln4+\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{1}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}+\frac{1}{2v_j}ln\frac{v_i^*}{v_j}\right)\right)\\
\frac{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i^*}{v_j}}{2v_i^*} &= \kappa ln4+\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{1}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}+\frac{1}{2v_j}ln\frac{v_i^*}{v_j}\right)\\
\frac{1}{v_i^*}+(1-ln(v_i^*))\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j} &= 2\kappa ln4+\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{2}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}-\frac{1}{v_j}ln(v_j)\right) && \text{(A.46)}
\end{aligned}$$

whereas equation A.46 is the condition for κ_i^{opt} maximizing visibility v_i^*. In the last step I verify that v_i^* constitutes a maximum by checking the second-order condition at this point:

$$\left.\frac{\partial^2 \kappa_i^{opt}}{\partial^2 v_i}\right|_{v_i=v_i^*} = \frac{-\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}}{\left(1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}\right)^2}\underbrace{\left(\frac{1}{ln4}\frac{1}{v_i}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{2v_j}-\kappa_i^{opt}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}\right)}_{=0}$$

$$-\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\left(\frac{1}{2ln4}\frac{1}{v_i^2}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}+\underbrace{\frac{\partial^2\kappa_i^{opt}}{\partial^2 v_i}}_{=0}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}\right)$$

$$= -\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\frac{1}{2ln4}\frac{1}{v_i^2}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}<0 \tag{A.47}$$

Now I check if $\tau_{i,r}^{2opt}$ is increasing in v_i:[5]

$$\frac{\partial\tau_{i,r}^{2opt}}{\partial v_i} = \frac{1}{\sigma_{i,s}^2}\left[4^{\kappa}\prod_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\sqrt{\frac{v_i}{v_j}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}}}$$

$$\left(\frac{1}{\left(\frac{1}{v_i}+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}\right)^2}\frac{1}{v_i^2}ln\left[4^{\kappa}\prod_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\sqrt{\frac{v_i}{v_j}}\right)^{\frac{1}{v_j}}\right]+\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}}\frac{1}{v_i}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{2v_j}\right)$$

$$>0 \tag{A.48}$$

For the comparative statics of v_i^* rewrite equation A.46

$$G=\frac{1}{v_i^*}+(1-ln(v_i^*))\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}-2\kappa ln4-\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{2}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}-\frac{1}{v_j}ln(v_j)\right)=0 \tag{A.49}$$

[5]If $y=x^x$ then $\frac{\partial y}{\partial x}=x^x(ln(x)+1))$

Taking the derivative of the parameters of interest from function G:

$$\frac{\partial G}{\partial v_i^*} = -\frac{1}{v_i^{*2}} - \frac{1}{v_i^*}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j} \tag{A.50}$$

$$\frac{\partial G}{\partial \kappa} = -2ln4 \tag{A.51}$$

$$\frac{\partial G}{\partial \sigma_{i,s}} = -\frac{2}{\sigma_{i,s}}\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j} \tag{A.52}$$

$$\frac{\partial G}{\partial \sigma_{j,s}} = \frac{2}{v_j\sigma_{j,s}} \tag{A.53}$$

$$\begin{aligned}\frac{\partial G}{\partial v_j} &= -\left(1-ln(v_i^*)\right)\frac{1}{v_j^2} + \frac{2}{v_j^2}\ln\left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\right) - \frac{1}{v_j^2}ln(v_j) + \frac{1}{v_j^2}\\ &= \frac{1}{v_j^2}\left(2ln\left(\frac{\sigma_{i,s}}{\sigma_{j,s}}\right) + ln\left(\frac{v_i^*}{v_j}\right)\right)\end{aligned} \tag{A.54}$$

Note that A.54 is negative iff $\frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} < \frac{v_j}{v_i^*}$ (, i.e. relation of the visibility of asset j to the visibility of asset i must be larger then the relation of the underlying variance of the signals send by sender s). With these derivatives at hand one can apply the implicit function theorem $\frac{\partial x}{\partial y} = -\frac{\frac{G}{\partial y}}{\frac{\partial G}{\partial x}}$ and determine the direction of the effect:

$$\frac{\partial v_i^*}{\partial \kappa} < 0 \tag{A.55}$$

$$\frac{\partial v_i^*}{\partial \sigma_{i,s}} < 0 \tag{A.56}$$

$$\frac{\partial v_i^*}{\partial \sigma_{j,s}} > 0 \tag{A.57}$$

$$\frac{\partial v_i^*}{\partial v_j} \quad \begin{cases} \geq 0 \text{ iff } \frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} \geq \frac{v_j}{v_i^*} \\ < 0 \text{ iff } \frac{\sigma_{i,s}^2}{\sigma_{j,s}^2} < \frac{v_j}{v_i^*} \end{cases} \tag{A.58}$$

A.7 Attention on asset i and changes in visibility v_j of asset j

$$
\begin{aligned}
\frac{\partial \kappa_i^{opt}}{\partial v_j} &= \frac{1}{ln4}\frac{1}{\left(1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}\right)^2}\frac{v_i}{v_j^2}\left(\kappa ln4+\sum_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{1}{v_j}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}+\frac{1}{2v_j}ln\frac{v_i}{v_j}\right)\right)\\
&\quad -\frac{1}{ln4}\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\left(\frac{1}{v_j^2}ln\frac{\sigma_{i,s}}{\sigma_{j,s}}+\frac{1}{2v_j^2}ln\frac{v_i}{v_j}+\frac{1}{2v_j^2}\right)\\
&= \frac{1}{2v_j^2}\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}}\left(2v_i\kappa_i^{opt}-2ln\frac{\sigma_{i,s}}{\sigma_{j,s}}-ln\frac{v_i}{v_j}-1\right) \qquad \text{(A.59)}
\end{aligned}
$$

Taking v_j^* as the point where $\frac{\partial \kappa_i^{opt}}{\partial v_j}=0$, the second order condition will be

$$
\left.\frac{\partial^2 \kappa_i^{opt}}{\partial^2 v_j}\right|_{v_j=v_j^*} = \frac{1}{2v_j^3}\frac{1}{1+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{v_i}{v_j}} > 0 \qquad \text{(A.60)}
$$

Thus v_j^* constitutes a local minimum.

A.8 Corner solution to asset i

Asset i will be neglected if there is no attention on it (, i.e. the correlation between the asset's dividend stream and the information processed R_i is zero). Therefore take equation A.35

$$
R_i^2 \leq 0 \iff 1 \leq \left[4^{-\kappa}\prod_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}\right]^{\frac{1}{\frac{1}{v_i}+\sum_{\substack{j\neq i\\ j=0}}^{I}\frac{1}{v_j}}} \qquad \text{(A.61)}
$$

$$
\iff 4^{\kappa} \leq \underbrace{\prod_{\substack{j\neq i\\ j=0}}^{I}\left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}}}_{H} \qquad \text{(A.62)}
$$

The following derivatives are straight forward:

$$\frac{\partial H}{\partial v_i} < 0 \tag{A.63}$$
$$\frac{\partial H}{\partial \sigma_{i,s}} < 0 \tag{A.64}$$
$$\frac{\partial H}{\partial \sigma_{j,s}} > 0 \tag{A.65}$$
$$\tag{A.66}$$

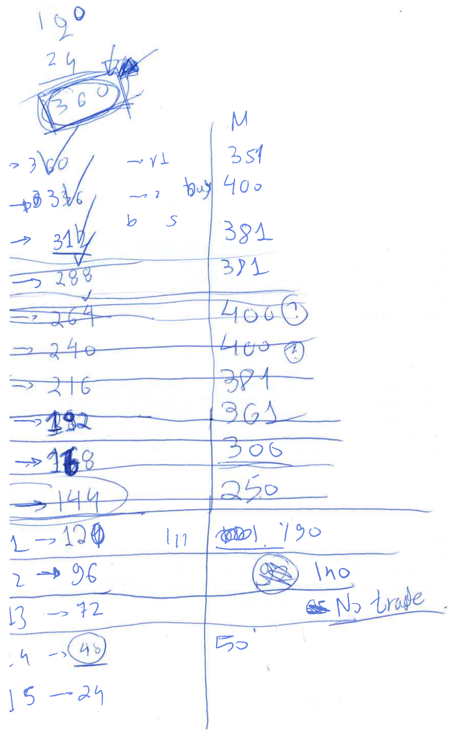
The derivative for v_j, with $j \neq i$ and $j \in I$, is more complicated. Taking the log(H) and then the derivative on v_j:

$$\frac{\partial H}{\partial v_j} = \frac{1}{v_j^2}\left[\frac{1}{2} - ln\left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)\right]\prod_{\substack{j \neq i \\ j=0}}^{I}\left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)^{\frac{1}{v_j}} \tag{A.67}$$

Thus as long as $\frac{1}{2} > ln\left(\frac{\sigma_{j,s}}{\sigma_{i,s}}\sqrt{\frac{v_j}{v_i}}\right)$ the derivative $\frac{\partial H}{\partial v_j} > 0$.

B Appendix: Chapter 2

B.1 Subject Notes



This figure shows the notes of subject made during the second phase of the experiment. As one can see, the subject calculated the expected value and wrote down the market price in the respective period. At one stage the subject calculated a fundamental value of 240 while the market price was 400. The subject itself could not make sense of it and noted question marks behind these prices.

B.2 Earnings per Task

Table B.1: Earnings per Experimental Tasks in CHF

Task	Average	Min/Max
Word Problems	1.12	0 / 2.1
Raven's Progressive Matrices	2.52	0.3 / 3.6
Game of Nim	0.78	0 / 1.5
Risk Attitude Test	9.62	0 / 30
Heider Test	3.60	1.5 / 5.4
Reading the Mind in the Eyes	3.21	1.2 / 4.5
Asset Market	29.14	6.04 / 53.4

B.3 Instructions 1st phase

Welcome

Thank you for participating in today's study.

In addition to a 10 CHF participation payment, you will be paid an amount of money accumulated from different tasks, which will be described to you during the study.

You will be paid privately, in cash, at the end of the study. The exact amount you receive will be determined during the study, and will depend on your decisions and sometimes on the decisions of the other participants.

Rules

During the study, **you are not allowed to communicate with the other participants**. If you have any questions, please raise your hand and an experimenter will come to assist you. Please do not ask other participants.

You will enter your decisions at your computer terminal. All interactions among participants will take place only through these computers. Please use the computers only as instructed.

Violation of these rules leads to immediate exclusion from this study. In this case, you will **not** receive **any** payments.

Instructions

This study consists of **several different parts**. Each part differs in duration. In the middle of the study, you will have a 15 minute break.

For each part, you will receive instructions. Please read them carefully since your payment will depend on how well you understand the instructions. For most parts, the instructions will be shown on the screen of your computer.

If you have any questions, please raise your hand.

B.4 Screening Tasks

B.4.1 Ravens Matrix

The Raven's Progressive Matrices Test is a non-verbal IQ-Test. We used the standard version of it (i.e., 12 items with increasing difficult level within a set of items). Therefore the participants had to exercise increasing cognitive analytic capacities to encode and analyse the information given. Within the task and experiment we did not provide any feedback on their performance. We only summarized this information for each task at the end of the whole experiment.

The participants received the following instructions: *"In this part of the study, you will see visual patterns. A part of each pattern is missing. For each pattern, you can choose the option that best completes the pattern. You will see 14 patterns. The first two are practice patterns. After the practices patterns, you will have 12 minutes to solve the remaining 12 patterns. For each of these 12 patterns that you solve correctly, you earn 0.30 CHF. "*

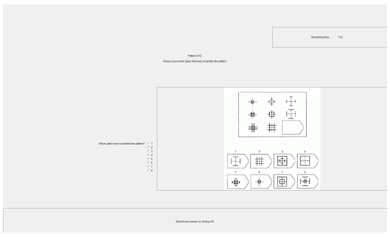


Figure B.1: Raven's Test sample screen

Thus the Raven's IQ-Test Version used here consisted of 12 items, incentivized with 0.30 CHF per correct answer, with a time restriction of 12 minutes for all items and measured two underlying abilities of the analytic capacities. (1) The deductive ability, requiring to think clearly and make sense of a complex scheme. (2) The reproductive ability, requiring to store and reproduce information.[1]

[1]For more information we refer to (Kline, 2013, p. 462ff).

B.4.2 Overconfidence Measure

Together with the Raven's Matrixes IQ-Test we measured overconfidence, by asking the subjects after the Raven's Test the following two questions:

1. Please estimate how many of the 12 patterns you completed correctly
2. Which group do you think you belong to?
   - Best 20%
   - 20% immediately below the best 20%
   - Middle 20%
   - 20% immediately above the worst 20%
   - Worst 20%

The screen looked like this:

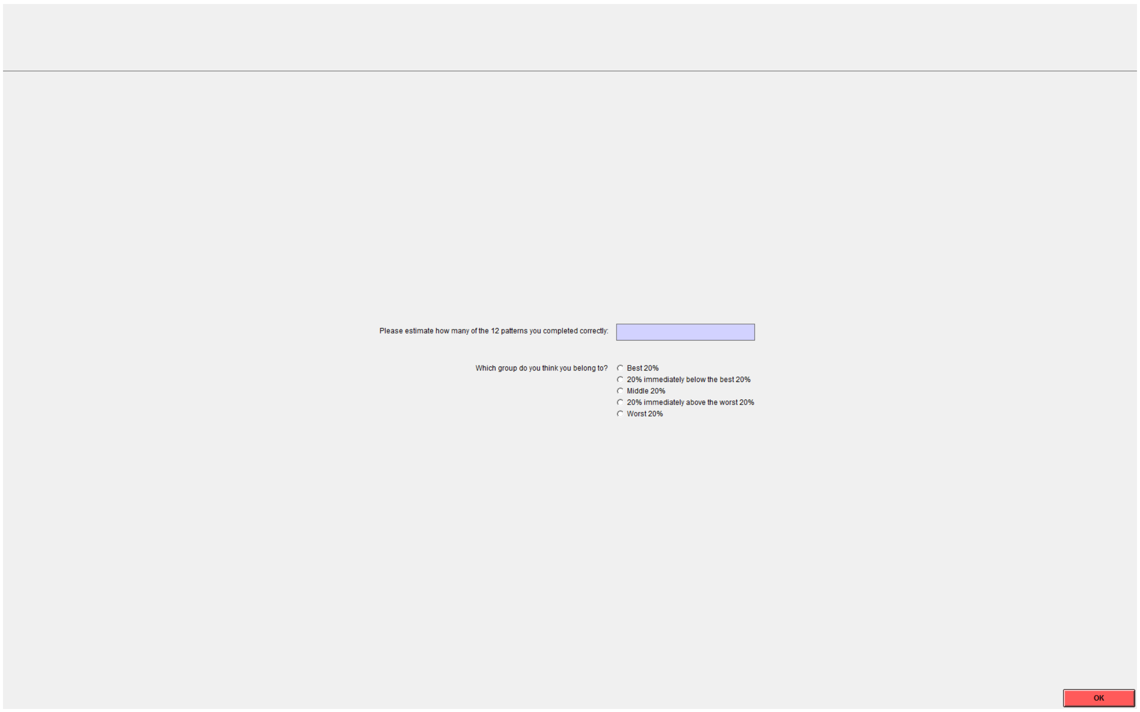


Figure B.2: Overconfidence measure screen

B.4.3 Game of Nim

The game of nim is a strategic game of two players taking turns removing objects from the board. In the version we used, the participants played against a computer, programmed to play best-response. The instructions where the following: *"On the following screens, you will play 5 mini-games against the computer. For each mini-game that you win, you will receive CHF 0.30 at the end of the session."*
"You will play a board game against the computer.
The Board:

The game board consists of rows of "stones".

Each row will be filled with 0-7 stones.

That is, some rows might be empty.

The Game:

You and the computer will take turns in removing the stones from the board.

You move first.

The computer is programmed to respond optimally to your actions.

To win, you have to be the one who removes the last stone from the board.
The Move:

When it's your turn, you remove stones from one row.

First, **you choose the row** from which to remove stones.

Then, you choose **how many stones** to remove from that row.

You can remove as many stones as you like in that row.

You must remove **at least one stone**, but you can remove more if you want.

After you have removed the stones from the row, it's the computer's turn.

The computer's move follows the same rules as yours.

Then the participants started to play the 5 games sequentially, with an increase in the level of difficulty. The subjects realized whether the won the game or not and faced the following board-screens, where they also found a summary of the rules of the game.

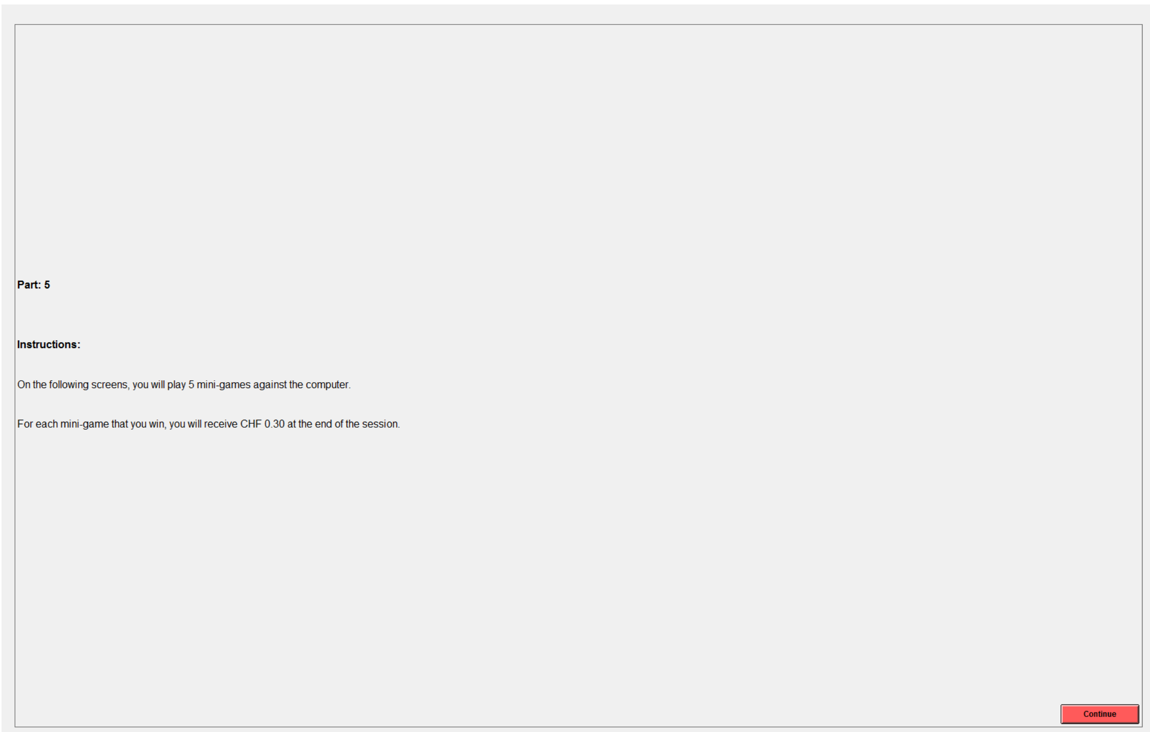


Figure B.3: Game of nim instruction screen number one

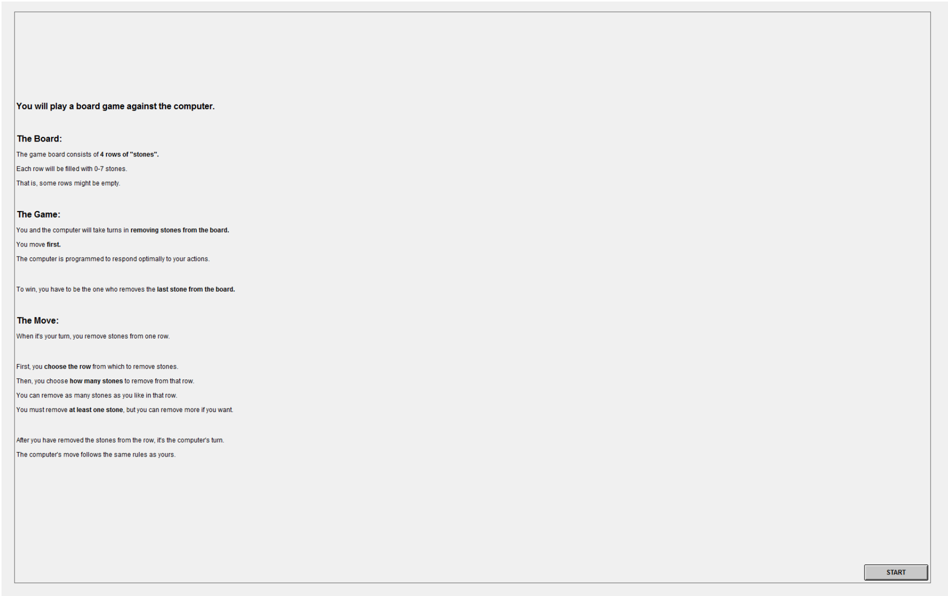


Figure B.4: Game of nim instruction screen number two

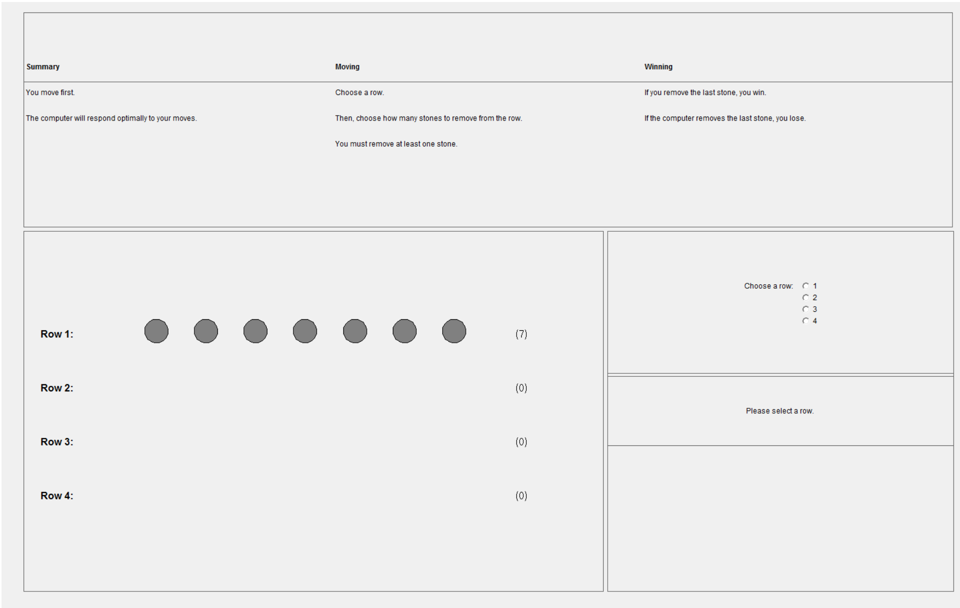


Figure B.5: Game of nim board one

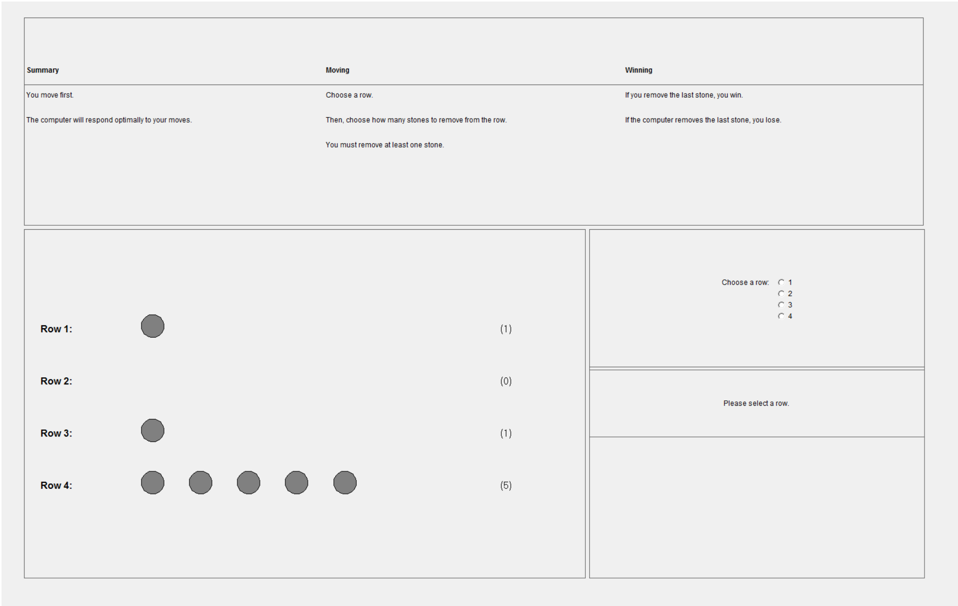


Figure B.6: Game of nim board two

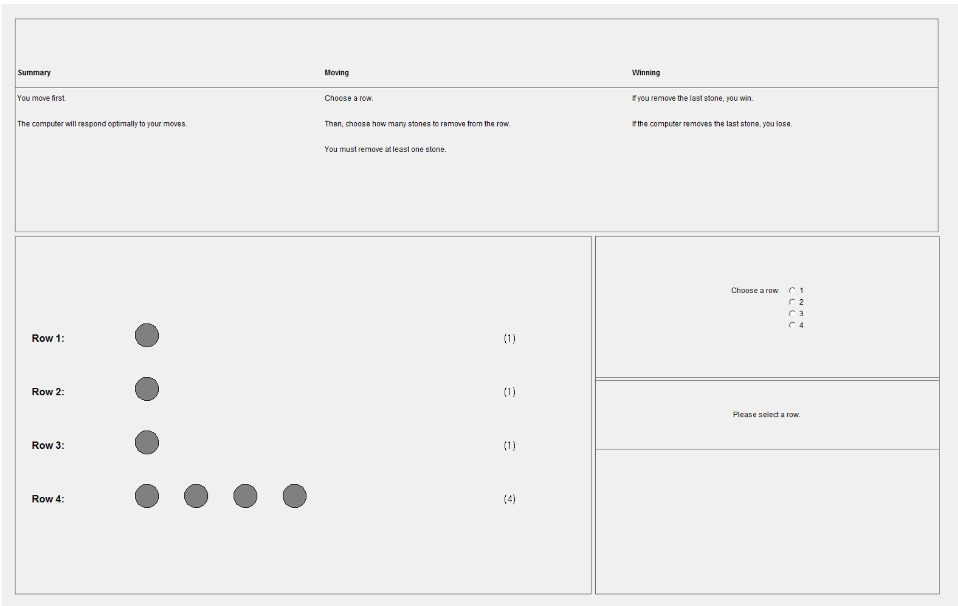


Figure B.7: Game of nim board three

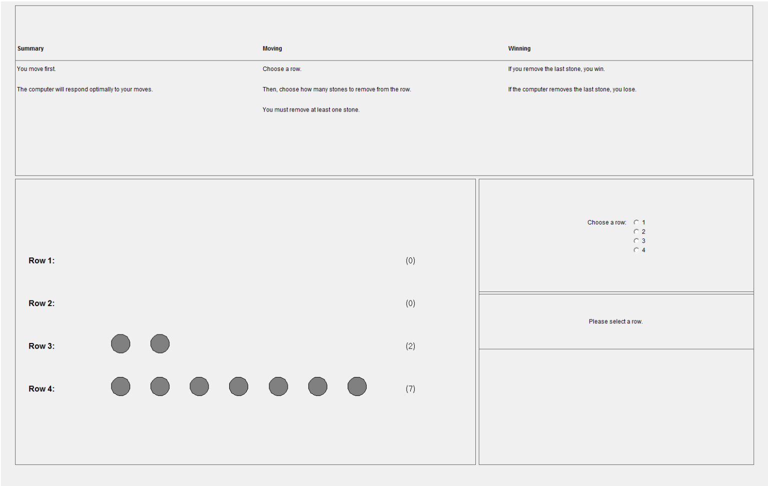


Figure B.8: Game of nim board four

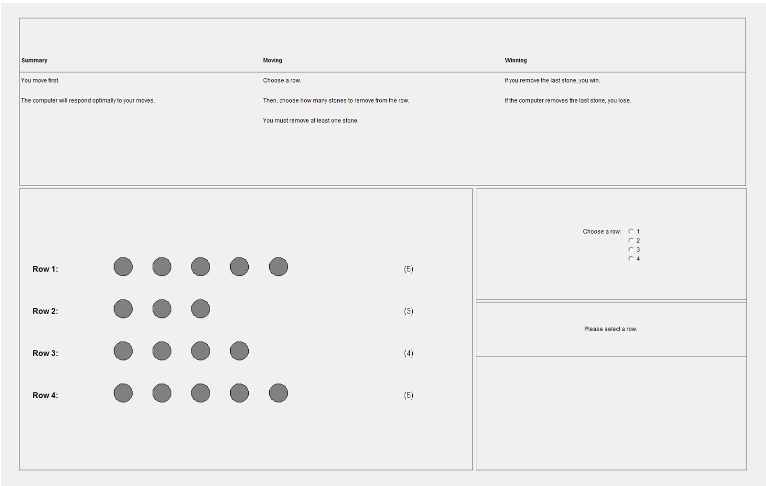


Figure B.9: Game of nim board five

Summarizing, the game of nim is a strategic board game, particularly employing the backward induction capacities of the subjects. We used 5 items, with increasing difficulty. There were no time restriction on solving each item. For each win, the subjects received 0.30CHF.

B.4.4 Test on Quantitative and Logical Reasoning

We presented subjects the following seven questions from a standard mathematics and logic questions of the type frequently used in Wall Street job interviews and used in experimental context by (Bruguier et al., 2010). Subjects had 60 seconds to type the answer and earned 0.30CHF per correct answer. Within the task and experiment we did not provide any feedback on their performance. We only summarized this information for each task at the end of the whole experiment.

The instructions were as follow: "Please answer the questions on the following screens. In the following, you will answer a series of quiz questions. Answer as many questions correctly as you can. You have 60s to answer each question. After the 60s you will be automatically directed to the next question. For every question that you answer correctly you will receive CHF 0.30 at the end of the experiment. Note in order to save your choice you have to PRESS THE OK BUTTON! Everything else counts as no choice. "

This is the list of the seven questions.

- Consider a game played with a deck of three cards: spades, clubs, and hearts. Your goal is to identify the hearts. The cards are shuffled and displayed in a row, face down. You make your choice. The dealer then turns over one of the two remaining cards, provided it is not hearts. He then offers you the possibility to change your choice and switch to the other card that is left face down. What is the best strategy? Should you switch, stay, or does it not matter?

  Options to choose: "switch", "stay" or "either".

  Correct answer: switch

- Consider a deck of four cards: spades, clubs, hearts, and diamonds. The cards are shuffled and displayed in a row, face down. You choose one card at random and it is discarded. Then the dealer turns over two cards, chosen at random, but provided they are not hearts. Now there is only one card left unturned. If the two cards the dealer turns over are diamonds and clubs, is the probability that the remaining one is hearts more than, less than, or equal to 0.5?

Options to choose: “more”, “less” or “same”.

Correct answer: More

- There are 8 marbles that weigh the same, and 1 marble that is heavier. The marbles are all uniform in size, appearance, and shape. You have a balance with 2 trays. You are asked to identify the heavier marble in at most 2 (two) weightings. How many marbles do you initially have to place on each tray?

  Input a number below.

  Correct answer: 3

- Divide 100 by 1/2. Is the result more, less than or equal to 100?

  Options to choose: “more”, “less” or “same”.

  Correct answer: More

- Jenn has half the Beanie Babies that Mollie has. Allison has 3 times as many as Jenn. Together they have 72. Does Mollie have more than, less than, or equal to, 20 Beanie Babies?

  Options to choose: “more”, “less” or “same”.

  Correct answer: More

- Johnny’s mother had three children. The first child was named April. The second child was named May. What was the third child’s name?

  Type the name below.

  Correct answer: Johnny

- The police rounded up Jim, Bud and Sam yesterday, because one of them was suspected of having robbed the local bank. The three suspects made the following statements under intensive questioning.

  Jim: I'm innocent.

  Bud: I'm innocent.

  Sam: Bud is the guilty one.

  If only one of these statements turns out to be true, who robbed the bank?

  Type the name of the robber below.

  Correct answer: Jim

We presented these problems similar in the following way:

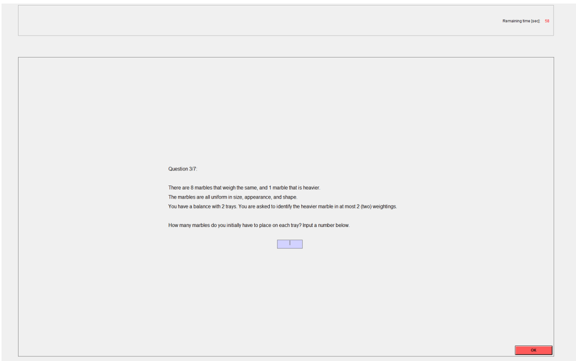
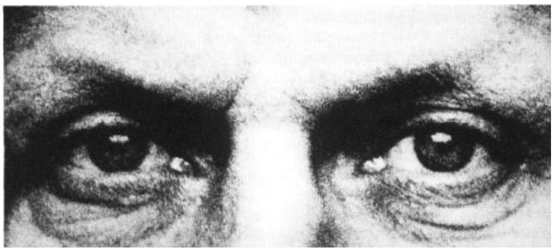


Figure B.10: Sample screen of the Quantitative and Logic Test

This 7 items test elicits the logical reasoning capacity as well as how well the participant can handle the quantitative aspect of a problem. It was incentivized by 0.30 CHF per correct answer and with time restriction. Bruguier et al. (2010) found no significant correlation between performance in this task and the ability to forecast price changes when there are insiders.

B.4.5 The Reading the Mind in the Eyes Test

The Reading the Mind in the Eyes Test (Baron-Cohen et al., 1997) shows participants a pair of eyes (e.g., figure B.12). The participant is asked to identify the emotions being most likely expressed among four options. We showed in February 2015 nine items to 64 participants and increased the number of items to 15 from then on (N=416).[2] There was no time constraint in answering the questions and the participant received 0.30CHF per correct answer. Within the task and experiment we did not provide any feedback on their performance. We only summarized this information for each task at the end of the whole experiment.



Options to choose from: ***serious***, *ashamed, bewildered, alarmed*

Figure B.11: Sample item from the Reading the Mind in the Eyes Test

The instructions are as follows: "Please answer the questions on the following screens. In the following, you will see pictures of people's eyes and you will be asked about what emotion they are expressing. In case needed you will find the German translation in brackets behind the english expression. Answer as many questions correctly as you can. For every question that you answer correctly you will receive CHF 0.30 at the end of the experiment."

The screens had the following look:

[2]Since we were not sure how familiar participants are with the vocabulary, we translated the four options in to German, which is the mother tongue of most of the participants in the subject pool. Here we used the suggested translation by Bruguier et al. (2010)

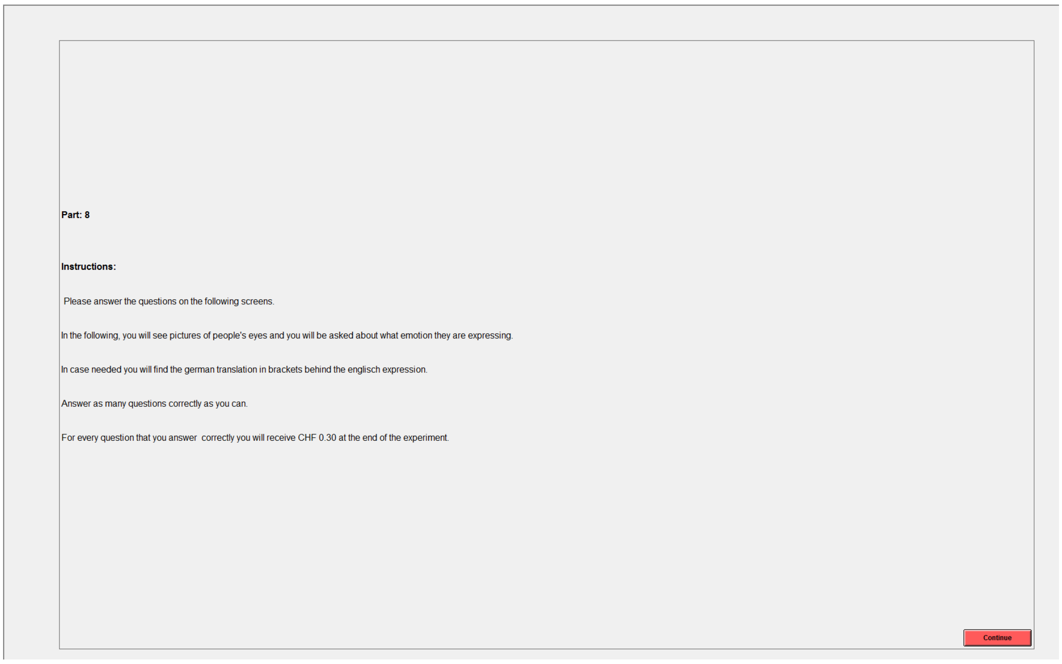


Figure B.12: Instruction to the Reading the Mind in the Eyes Test

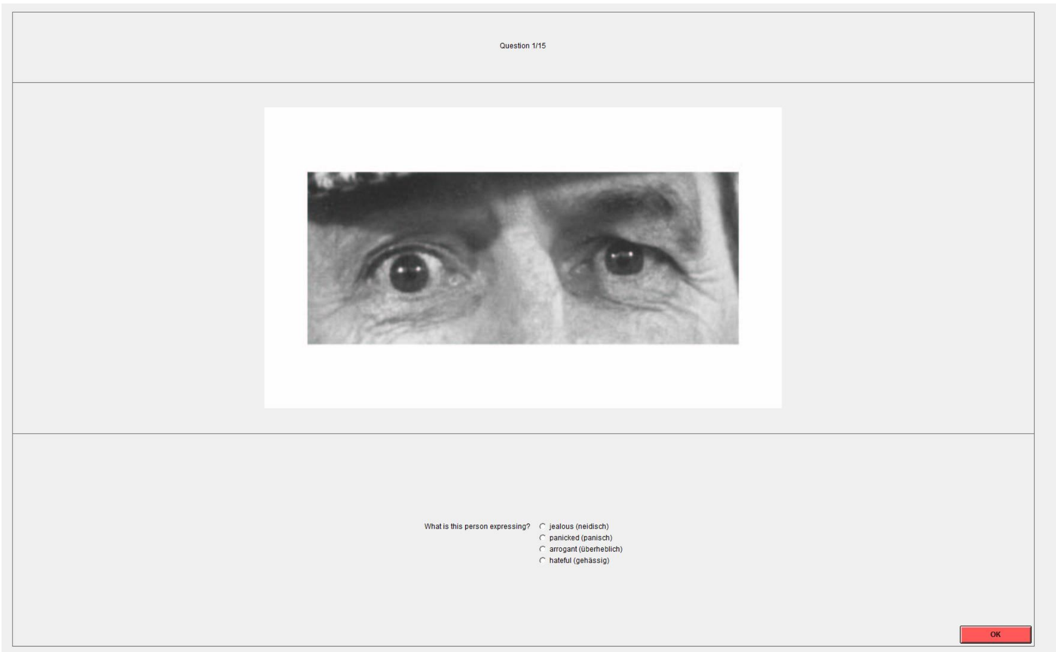


Figure B.13: Sample screen of the Reading the Mind in the Eyes Test

The Reading the Mind in the Eyes test is used to diagnose high-functioning adult autism.[3] The lower the performance in this test, the higher the likelihood of an autism

[3]Such as the Asperger's Syndrome

disorder. Moreover, psychology research indicates, that people with autism perform worse than a controlled group in test on cognitive empathy, and show on average the same results when tested on emotional empathy (Dziobek et al., 2008). Thus autism is more a problem about to infer about others intention, rather then on their emotional state. Therefore the Reading the Mind in the Eyes test seems to be suitable approximation for cognitive empathy capacities.

A good performance in the Reading the Mind in the Eyes test is associated with the ability to detect whether or not price movements in an asset market are affected by traders with superior insider information (Bruguier et al., 2010).

B.4.6 Heider-Simmel Task

The Heider-Simmel-Task consists of two 20s and 60s long videos with geometric shapes moving on a plane imitating social interaction. It tests the ability to read intention or goal-directness of others. We stopped the videos every five seconds and asked the participants to predict whether two of the shapes would get closer, further apart or keep the same distance at the end of the upcoming five seconds sequence. Figure **??** and **??** show the screen shots after 20 and 25 seconds as an illustrative example of this task for the first video. For each answer the participants had 5s times. Thus similar to Bruguier et al. (2010) we ran this as an forecasting exercise with a reward of 0.30 CHF for each correct answer. Within the task and experiment we did not provide any feedback on their performance. We only summarized this information for each task at the end of the whole experiment.

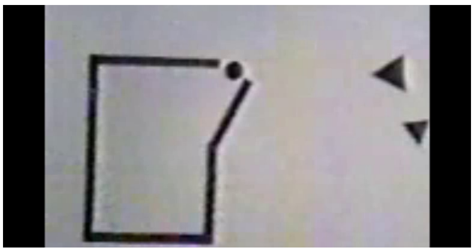


Figure B.14: Screenshots after 20s

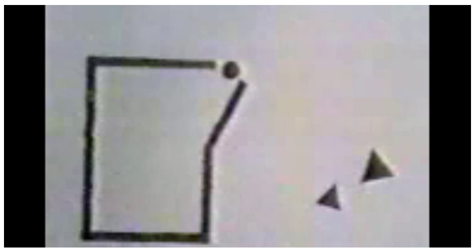


Figure B.15: Screenshots after 25s

The instructions for the both videos were displayed immediately before each video and read as follows: *"You will watch two movies of three geometric objects: A circle, and two squares or two triangles, one small and the other one large. The objects move around, into, inside, and out of a box. In the first (second) movie, with a circle and two triangles (squares), your task is to* ***predict the movement of the large triangle (square).*** *The movie will be stopped after 5 seconds. You then have 5 seconds to predict where the large triangle will be after another 5 seconds of the movie. Specifically, is the large triangle going to be closer to or farther away from the small triangle than at present? After your choice, we play the movie for another 5s, stop the movie again, after which you are again* *asked to predict the movement of the large triangle, etc. We will continue these cycles until the end of the movie. Answer as many questions correctly as you can.* ***Remember: you have 5 seconds for each answer.*** *For every question that you answer correctly you will receive CHF 0.30 at the end of the experiment. Note in order to save your choice you have to PRESS THE OK BUTTON! Everything else counts as no choice."*

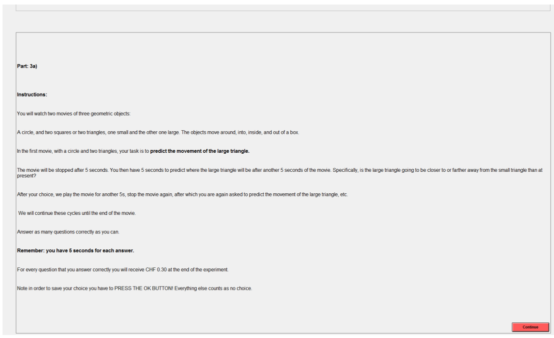


Figure B.16: Heider-Simmel-Test Instruction to the first video

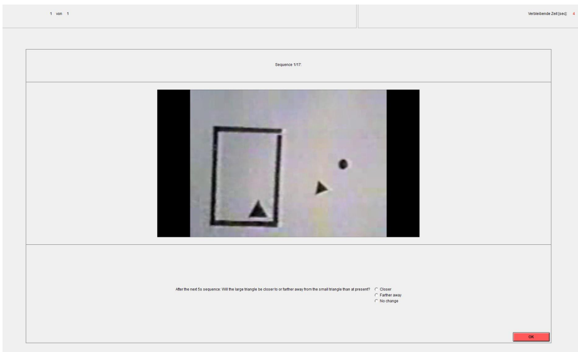


Figure B.17: Heider-Simmel-Test sample screen of the forecasting task in the first video

Originally the Heider-Simmel-Test (Heider and Simmel, 1944) is executed differently by asking the participants several question to describe the observed situation and thus relying on verbal evidence of anthropomorphizing to determine to which extent a participant engages in theorizing about the intentions of the geometric figures.[4] Since this approach involves some subjective interpretation of the examiner, we follow Bruguier et al. (2010) with a more direct and objective approach. It is (1) direct, since it only asks for

[4] A very amusing video about US-comedians participating in the Heider-Simmel-Test can be found on youtube.

an prediction of the movements, thus anthropomorphizing is not necessary for a good performance in this task, in general anthropomorphizing is sufficient for mentalizing, but not necessary. Furthermore the chosen approach (2) avoids to rely on a verbalization, which might led to misinterpretation. Finally (3), it is a performance based measure and also agrees with the standards of experimental economics, since we paid for performance. We had some difficulties with displaying few movie sequences on the screen. So some subjects couldn't see them and thus couldn't answer the question. Therefore we decided only to evaluate these questions, that have been answered by the subjects, and ignore unanswered ones, independent of whether they have been intentionally unanswered or by the displaying problem.

Bruguier et al. (2010) point out that self-reports after their experiment indicate a high degree of personalization (anthropomorphization) in the Heider-Simmel-Task, but barely any evidence in their Financial Markets Prediction task. Participants in the Heider-Simmel-Test with autism show a significant lower tendency to anthropomorphizing the description than normal developed adolescents (Castelli et al., 2002; Klin, 2000) Similar to the Reading the Mind in the Eyes Test the performance in the Heider-Simmel-Task positively correlates with the ability to forecast price changes when insider are present in the experimental asset market (Bruguier et al., 2010).

B.4.7 Risk-preference

The risk-preferences are assessed by a choice tasks similar to Holt and Laury (2002). The participants are confronted with a decision table with 20 decisions two make between option A receiving a fix amount and option B a lottery with CHF 0 or CHF 30 as equally likely outcomes. Each decision was presented in one row, and the certain amount increase from row to row, while the lottery was always the same. This approach allows us to determine the certainty equivalent of the subject and thus compare relatively the degree of risk-aversion of the subjects.
The instructions are as follows: *"On the following screen, you will make several choices. Depending on these choices, you may receive an additional payment at the end of the session. In this task you choose between two payments, an* ***"certain"*** *payment or a* ***"uncertain"*** *payment. The left choice is the certain payment. If you choose this payment, we will mail you the specified amount. The right choice is the uncertain payment. If you choose this payment, the payment will be determined by an electronic coin flip. That is, if you choose the uncertain payment, you will either receive CHF 0 or CHF 30. Each event will happen with equal probability, depending on the outcome of the coin-flip. Below, you see 20 rows. Each row is a decision between a certain and an uncertain payment. The amount of the certain payment varies from row to row. Please make a choice between certain and uncertain payment* ***for each of the 20 rows.*** *At the end of the session, the computer will choose* ***one*** *of the 20 rows at random. Your choice in this row will determine your payment. "*

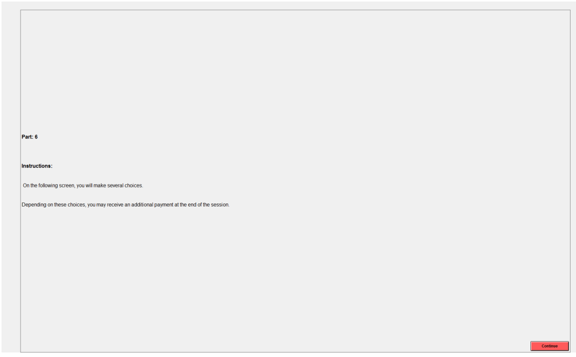


Figure B.18: Risk-preferences instruction screen

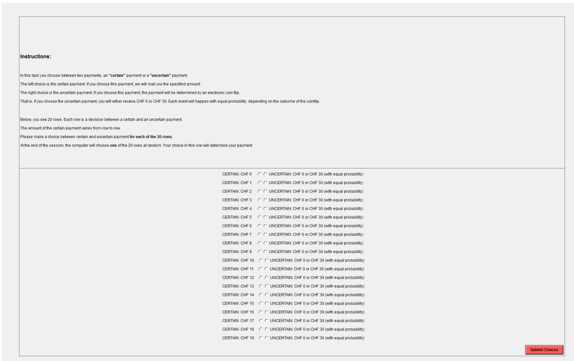


Figure B.19: Risk-preferences decision screen

Dohmen et al. (2010) find that individuals with higher analytic capacities, measured by two sub-modules of the Wechsler Adult Intelligence Scale, take significantly risk in the Holt-Laury-lottery task, this relation is independent from age and sex. This is in line with the recent work on the subjective component in the perception of risk (e.g., Andersen et al. (2014); Harrison et al. (2015)) and the evaluation of the consequences between a lottery and a certain amount might be more clear to a participant with higher analytic capacities.

B.5 Instructions 2nd phase

Instructions

I will now read through a script to explain to you the nature of the following task, as well as the computer interface through which you will enter your decisions. I will use this script to make sure that the information given in all sessions of this study is the same.

If you follow the instructions carefully you are able to earn money, which will be paid out at the end of the study. All interactions take place via your computer interface. Use the computer only as instructed. If there are any questions, please raise your hand and an experimenter will come to assist you. Please do not ask other participants. If you violate the rules, you will have to leave the study without any payments.

These instructions contain numerical examples. The numbers shown are **fictitious** and serve only to illustrate the task. In the actual study, you will face situations that differ from the examples used here.

Overview

For this part of the study, all participants are separated into **two independent groups** of 16 participants each. All interactions take place only within this group.

This part of the study consists of a task that is divided into 15 periods. In each period, you will make decisions. At the beginning of the task, you will be given an account with some **cash**. The amount of cash is shown in Rappen. On a second account, you are given some units, or **"shares," of an "asset."**

Each period consists of two phases:

Phase 1:

At the beginning of each period, you can trade shares and money with the other participants. Specifically, you can:

- **buy shares** from other participants; this will increase the number of shares you own and decrease the amount of cash in your account;
- **sell shares** you own to other participants; this will decrease the number of shares you own and increase the amount of cash in your account.

Phase 2:

After all participants have specified their buy and sell orders in the current period, the asset generates a random amount of money to everybody who owns shares. Specifically, this amount can be **0, 8, 28, or 60 Rappen per share**. At the end of the period, the computer randomly determines which of these four amounts is paid out in the current period, and adds the money to the cash account of all share owners. Each of the four amounts is equally likely in every period. After this, the results of the period are shown and the next period starts.

Phase 1: Market Phase

During the "Market Phase" you can trade shares and cash indirectly with the other participants via the computer. You do this by giving sell and buy orders to the computer. We will now explain how selling and buying works.

At the beginning of each period, you are shown the amount of cash and the number of shares that you currently own. Then, you enter both a "**sell order**" and a "**buy order**." In the sell order, you specify the minimal price at which you are willing to sell a number of shares you own in return for cash. In the buy order, you specify the maximal price at which you are willing to buy shares. The computer then aggregates all orders from all participants and computes a **"market price**" at which shares will be sold and bought.

Sell Order

A sell order consists of two numbers, a sell price and a sell quantity:

- First, you enter the **minimum sell price** that you demand in exchange for one of your shares;
- Then, you enter the **maximum number of shares** you would like to sell at this price.

Buy Order

A buy order also consists of two numbers, a buy price and a buy quantity:

- First, you enter the **maximum buy price** you are willing to pay for getting an additional share;
- Then, you enter the **maximum number of shares** you would like to buy at this price.

Whether you buy or sell shares in a given period depends on the orders you made and the market price. If the market price is **below** your maximum buy price, you **buy** shares. That is, you buy the number of shares you have specified in the buy order, at the **market price**. If the market price is **above** your minimum sell price, you **sell** shares. That is, you sell the number of shares you specified in the sell order, at the **market price**. If the market price is in between the two prices you stated, then you do not trade in this period.

If you don't want to sell (buy) any asset, you can leave the sell (buy) order blank. In that case, you will not sell (buy) shares in this period, regardless how high (low) the market price is.

Market Price

All participants make their sell and buy orders simultaneously. The computer then **collects all orders and uses them to determine the market price.** All shares that are traded in this period are bought and sold at this price. The computer automatically chooses a price that allows a maximum number of shares to be traded. Then, the computer transfers cash and shares between participants according to their orders and the market price.

If the market price is *exactly* equal to your maximum buy price, the computer may not be able to fully complete your buy order. That is, the number of shares you buy may be lower than the number you specified (as there may not be enough shares left for sale).

If the market price is *exactly* equal to your minimum sell price, the computer may not be able to fully complete your sell order. That is, the number of shares you sell may be less than the number you specified in the sell order (as there may be not enough shares left for purchase).

Example:

We will now go through a fictitious example of phase 1 on the screen. You will proceed by clicking the continue button in the bottom right corner. **Only click the button when instructed to do so!**

Please click "**Continue"** now to get to the next screen.

Your Current Account: The first row of the screen tells you how much cash you currently own; the second row tells you how many shares of the asset you currently own. In this example, you currently have 1000 Rappen and 2 shares of the asset.

Sell Order: In the lower part, you can enter your sell order (left) and your buy order (right side). Please enter the following sell order: you are willing to sell shares if the market price is **at least 300 Rappen per share**; and you are willing to **sell up to 3 shares**. Then click "Submit sell order." You see a message that you cannot submit this order because you own only 2 shares (you would need at least 3 shares for this order). Please change the number of shares in the order to 2. Then, click "Submit" again. The pop-up message asks you to confirm your order. Click "Yes."

Buy Order: Now, enter the following buy order: you are willing to buy shares if the market price is **200 Rappen per share**, or less; and you are willing to **buy at most 6 shares**. Then click "Submit buy order." You see a message that you cannot submit this order because you have only 1000 Rappen (you would need at least 200 x 6 = 1200 Rappen for this order). Please change the number of shares to 4. Then, click "Submit" again. Click "Yes" in the pop-up message. To confirm both orders, click the red "Submit orders" button.

Case 1: Market price = 350 Rappen

The computer collects the orders of all participants and then computes a market price. Suppose that, in this fictitious case, the computer calculated a market price of 350 Rappen per share. You see the market price at the top of the screen. That is **higher than the minimum price** at which you were willing to sell, 300 Rappen per share.

Shares: That means that you sell 2 shares, the number you specified in your sell order. The number of shares you own decreases from **2 to 0 shares**, as you can see on the left side of the screen.

Cash: You receive 2x350 = 700 Rappen in exchange for the shares. That means that the amount of cash you own increases from 1000 to 1700 Rappen. You can see this on the right side of the screen.

Please click **"Continue"**

Case 2: Market price = 250 Rappen

In this example, the computer calculated a market price that is higher than the maximum price at which you were willing to buy, so you **don't buy**. The market price is also lower than the minimum price at which you were willing to sell your shares, so you also **don't sell**. This means that the number of shares you own remains the same (2), and the amount of cash also remains at 1000 Rappen.

Please click **"Continue"**

Case 3: Market price = 150 Rappen

In this case, the computer calculated a market price of 150 Rappen per share. Since this is below your maximum buy price of 200 Rappen, you buy 4 shares, as specified in your buy order. For these 4 shares, you pay a total of 4x150 = 600 Rappen. That means that the number of shares you own increases from 2 to 6, and the amount of cash you own decreases from 1000 to 400 Rappen.

Restrictions

- You can only submit one sell order and one buy order per period
- You cannot sell more shares than you currently own.
- You cannot buy shares for more cash than you currently own
- Your maximum buy price must be lower than your minimum sell price.
- Prices must be whole numbers (for example, a price of 10.5 is not allowed)

Summary Market Phase:

- You enter a sell order and a buy order
- The computer determines the market price
- According to your orders and the market price, you either
    - (a) buy shares (market price **below** your maximum buy price)
    - (b) sell shares (market price **above** your minimum sell price)
    - (c) do nothing (market price in between)
    - This figure illustrates when you buy and when you sell:

- If you don't want to sell (buy) shares at all, you can leave the sell (buy) order blank
- If you buy, you will **never** pay more than your maximum buy price
- If you sell, you will **never** receive less than your minimum sell price
- If you sell/buy shares, you **always receive/pay the market price**
- Most of the time, you sell/buy the number of shares that you specified in the order
- Sometimes, you sell/buy fewer shares, when your order price *exactly equals* the market price

Do you have questions about the market phase?

Phase 2: Dividend

After the computer has completed all transfers of cash and shares between participants, phase 1 of the current period is finished. Now, in phase 2, the computer determines the amount of cash that the asset generates in the current period. That is, the computer randomly chooses one of four possible amounts: 0, 8, 28, or 60 Rappen per share. We call this amount "**DIVIDEND.**"

The dividend comes **on top of the amount** of cash you had at the end of the market phase. Once the computer has determined the amount of the dividend, it will be added automatically to your cash. After that, the current period is completed and the next period begins.

In each period, each of the four amounts is **equally likely** to be chosen. This means that, on average, over many periods, you can expect a dividend of 24 Rappen per share and period.

Example:

Please click **"Continue."** In the lower right part of the screen you see the outcome of the dividend phase. In this fictitious example, the computer has randomly chosen the amount of 8 Rappen per share for this period. In case 3, you own 6 shares at the end of the period. That means that, in phase 2, the computer adds a total dividend of 6 x 8 = 48 Rappen to your cash account, and you leave the period with a total amount of 448 Rappen.

Final Payoff

In phase 2 of period 15, the computer will determine a final dividend (0, 8, 28, or 60 Rappen per share). This amount will be multiplied by the number of shares you own at the end of period 15, and then added to your cash account. The account will then be closed and the final amount of cash will be added to your payments from the other parts of the study. Note that after that point, the shares you own will be worthless, that is, only the amount in your cash account at the end of period 15 is relevant for your payment.

Summary

- This part is divided into **15 periods**.
- You start out with a certain amount of cash and a certain number of shares
- In each period, you can submit buy and sell orders to **trade** shares with other participants
- After the market phase, each share generates a random cash payment, the **dividend**
- You can earn money both from trading shares, and from the dividends generated by the shares you own

Please raise your hand if you have any questions.

We will now show you a couple of comprehension questions to make sure that the instructions are clear to everybody. Click "Continue" to see the questions.

B.6 Comprehension Question

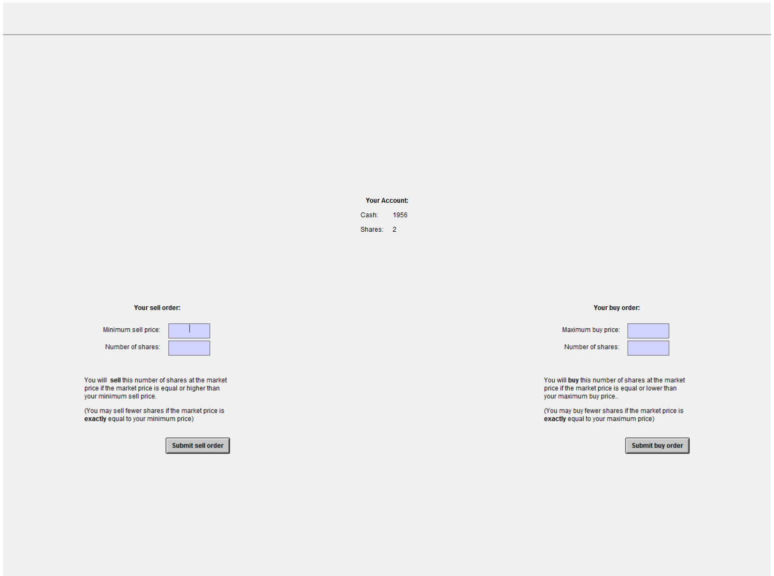
1 At the beginning of period 11, how many future dividend draws can you expect?

2 What are the maximum earnings you can expect from total dividend payments, if you hold **5** shares from the **beginning of period 11** until the **end of period 15** (no selling or buying of new shares

3 At the end of the market phase of period 15, you own 2674 Rappen in cash and 1 share. The dividend draw in period 15 was 8 Rappen per share. How much cash do you have at the end of period 15, and what will thus be your earnings from this part of the experiment?

4 At the beginning of a period, you have 2500 Rappen cash and 6 shares. You submit a buy order of 4 shares at a maximum buy price of 250 Rappen. Your sell order is 1 share at a minimum sell price of 500 Rappen. At the end of the market phase, the computer determines a market price of 400 Rappen. The dividend at the end of the period is 28. How much cash do you have at the end of this period after the dividend payment?

B.7 Asset Market



Trading Screen

B.8 Final Questionnaire

Asset Market: (*Trading Strategy*)

In the last part of this study, you could trade an asset on an asset market.

Please explain briefly your considerations how you aimed to make profits through trading.

5 questions from the Financial Literacy Test

FinLit1 Assume a friend inherits $CHF 10,000$ today and his sibling inherits $CHF 10,000$ 3 years from now. Who is richer because of the inheritance?

FinLit2 Which of the following statements is correct? If somebody buys the stock of firm B in the stock market:

- He owns part of firm B

- He has lent money to firm B
- He is liable for firm B's debts
- None of the above
- Do not know

FinLit3 Considering a long time period (for example 10 or 20 years), which asset normally gives the highest return?

- Savings accounts
- Bonds
- Stocks
- Do not know

FinLit4 Normally, which asset displays the highest fluctuations over time?

- Savings accounts
- Bonds
- Stocks
- Do not know

FinLit5 When an investor spreads his money among different assets, does the risk of losing money:

- Increase
- Decrease
- Stay the same
- Do not know

Socio-Economic Information

Highest Degree: What is your highest finished degree so far?

Current Degree: What is your current degree program (if you are not studying, please type in your highest degree program):

Semester Which semester are you in your degree program (If you are not studying, please type in how many semesters you studied for your highest degree)?

Studienrichtung: Field of study (major)

nationality: Nationality

Language: Native language

gender: Gender

age: Age

Studienintreesse: How interesting was the study for you? (Scale 0 to 7)

Anleitung: Were the instructions clear to you?

- very clear
- somewhat clear
- somewhat unclear
- very unclear

TeilnahmeWP: Have you ever participated in an experiment on asset markets? (Yes/No)

AktienhandelJa: Have you ever actively traded stocks? (Yes/No)

Aktienhandel: How many times did you trade stocks or other assets within the past 12 months? (Guess)

freqHoroscope: On average, how often do you read your horoscope?

- Every day
- Once per week

- Once per month
- Once per year
- Never

donateRel: Within the past two years, have you donated money to a religious institution or a religious aid organization? (Yes/No)

believeJustice: Do you believe in a higher justice in life (such as destiny, karma)? (Yes/No)

Risk How would you describe yourself:

patience: Are you generally an impatient person, or someone who always shows great patience? (Scale from 0 - 10)

impulsiveness: Do you generally think things over for a long time before acting - in other words, are you not impulsive at all? Or do you generally act without thinking things over for long time - in other words, are you very impulsive? (Scale from 0 - 10)

risk1: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (Scale from 0 - 10)

You can behave differently in different contexts. How would you assess your willingness to take risks in the following areas?

risk2: When driving a car? (Scale from 0 - 10)

risk3: With financial matters? (Scale from 0 - 10)

risk4: With sports and leisure? (Scale from 0 - 10)

risk5: With your professional career? (Scale from 0 - 10)

risk6: With your health? (Scale from 0 - 10)

risk8: Imagine you won CHF 100,000 in a lottery. Almost immediately after you collect your winnings, you receive the following financial offer from a reputable bank, the conditions of which are as follows:

- There is the chance to double the money within two years.
- It is equally possible that you could lose half of the amount invested.

Which part of the CHF 100’000 would you allocate to the risky but profit-promising investment?

- The whole amount of CHF 100’000
- CHF 80,000
- CHF 60,000
- CHF 40,000
- CHF 20,000
- nothing, I would decline this offer

B.9 Addition Results and Robustness Checks

B.10 Robustness Check on Trading Gains under varying Quantiles

Table B.2: Regression analysis trading gains across cognitive types with separate quantiles

	Median Split	q40	q30
A-high	34.783	-123.738	199.463
	(184.485)	(257.203)	(319.115)
M-high	-424.671***	-297.823	-662.215
	(135.139)	(228.790)	(394.255)
A*M	855.236***	852.409***	761.230
	(218.973)	(308.460)	(466.805)
Constant	-4.034	23.617	7.481
	(72.013)	(110.895)	(157.121)
adj. R^2	0.052	0.044	0.057
N	256	157	85

OLS regressions, standard errors in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
qX is the Xth-quantile for setting the dummy for the respective cognitive capacity.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Trading gains for entire asset market phase, in Rappen.
Independent variables: Constant: baseline category. "A-high:" dummy taking the value 1 if the participants performance belonged to the upper Xth-quantile in the A dimension and zero if the performance belonged to the lowest Xth-quantile; 'M-high:" dummy taking the value 1 if the participants performance belonged to the upper Xth-quantile in the M dimension and zero if the performance belonged to the lowest Xth-quantile; "A*M:" interaction between A-high and M-high.

B.11 Comparison of coefficients on Buy- Sell-offer Prices

Figure ?? reports the mean buy order prices (lines below the average market price) and mean sell order prices (lines above the average market price) for each type. We classified sell-order-prices above 2000 Rappen and buy-order-price at zero as not serious orders and ignored them for this figure.

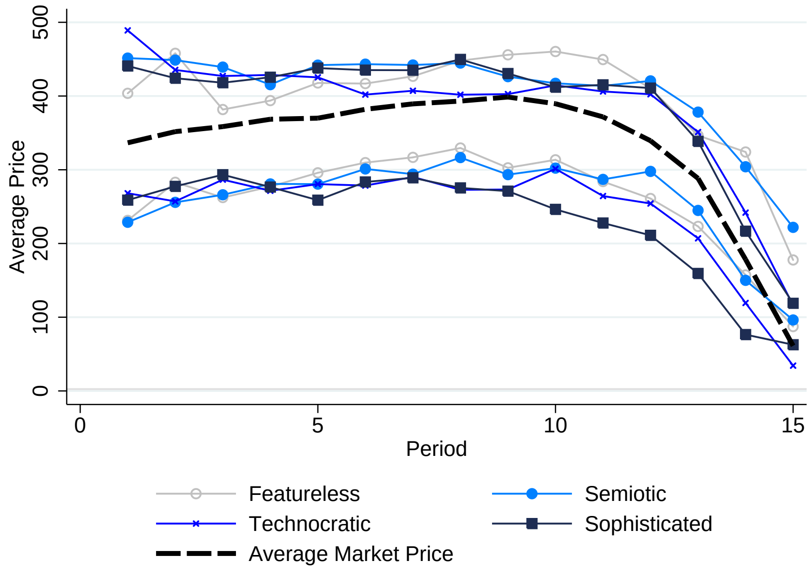


Figure B.20: Mean order prices by cognitive types
This graph shows the average market price (dashed line), mean buy order prices (lines below the average market price) and mean sell order prices (lines above the average market price) per cognitive type. We classified sell-order-prices above 2000 Rappen and buy-order-price at zero as not serious orders and ignored them for this figure.

Testing for differences in the valuation we run regression analysis reported in table B.3. The first column compares the coefficients of equation (2.1) for featureless against the semiotic types. For this we pooled the data of both types and repeated the regression from table 2.9. A dummy for belonging to one type was introduced and multiplied with both components. This allows to disentangle the additional effect of the specific type and judge whether this difference is significant. For example, the dummy for semiotic type d_{SE} separates the additional effects on the coefficients for the semiotic types, thus if

$d_{SE} = 0$, one receives the equation (2.1) estimate for the featureless type, as presented in table 2.9. The negative insignificant coefficient on the interaction term of the semiotic-type-dummy and the fundamental value implies we are not able to reject the Null, that the coefficients for both types are the same for the fundamental. The same holds true for the differences on the interaction term between the semiotic-type-dummy and the last period price. The second and third column compare the featureless types with the technocratic and semiotic types: Both types have a significant higher coefficient on the fundamental value and a lower coefficient for the last period price, however this effect is not significant. Turning towards comparing the semiotic type with both types high on the A-dimension (, i.e. column four and five respectively), the differences in the coefficients on the fundamental value are in the right direction and significant. However, even though the differences on coefficients for the last period price have the predict sign, these differences are not significant, which we expected for a comparison of the semiotic and sophisticated type, but not for semiotic vs. technocratic types. The last column in table B.3 reports the comparison technocratic vs. sophisticated types. The results do not show any significant differences in behaviour, which we expected for fundamental value, but not for the coefficient on the last period price. Moreover the difference in the effect are reverse to what we expected, the technocrat has a larger weight on the last period price than the sophisticated-type and a lower one on the fundamental value.

Table B.3: Comparison of types - Willingness to buy

	FL vs. i=SE	FL vs. i=TE	FL vs. i=SO	SE vs. i=TE	SE vs. i=SO	TE vs. i=SO
FV_t	0.259***	0.259***	0.259***	0.174***	0.174***	0.478***
	(0.051)	(0.050)	(0.052)	(0.044)	(0.044)	(0.068)
p_{t-1}	0.797***	0.797***	0.797***	0.801***	0.801***	0.639***
	(0.056)	(0.056)	(0.056)	(0.091)	(0.091)	(0.096)
d_i*FV_t	-0.085	0.219***	0.349**	0.304***	0.432***	0.128
	(0.065)	(0.078)	(0.119)	(0.080)	(0.111)	(0.129)
d_i*p_{t-1}	0.012	-0.157	-0.255	-0.168	-0.257	-0.087
	(0.071)	(0.095)	(0.195)	(0.112)	(0.18)	(0.202)
d_i	3.72	-12.57	-9.98	-16.14	-16.64	-0.994
	(31.3)	(27.03)	(41.72)	(33.014)	(37.40)	(38.40)
Constant	-70.68***	-70.57***	-71.06***	-66.38**	-66.52**	-82.56***
	(25.00)	(24.99)	(25.08)	(31.36)	(31.40)	(22.69)
R^2-overall	0.216	0.264	0.282	0.26	0.28	0.338
Observations	1611	1513	1527	1270	1284	1186

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participant. Data from both groups under consideration is pooled for the specific regression.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Willingness to pay for each period
Independent variables: "FV:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16 - t) * 24$; "p_{t-1}:" Price in the last period. "d_i:" Dummy for i-type; $d_i = 1$ if participant is of type i, zero otherwise..

Table B.4: Willingness to accept per type

	FL	SE	TE	SO
FV_t	-0.084	0.251***	0.801*	0.373***
	(0.199)	(0.097)	(0.415)	(0.127)
p_{t-1}	0.621	1.177***	0.933***	1.204***
	(0.432)	(0.296)	(0.190)	(0.124)
Constant	207.773	-16.715	189.585	-119.367***
	(171.049)	(93.924)	(198.883)	(42.359)
R^2-overall	0.008	0.025	0.002	0.354
N	806	620	415	389

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Willingness to accept for each period
Independent variables: "FV_t:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16 - t) * 24$; "p_{t-1}:" Price in the last period.

Table B.4 shows that for all types the estimated α_1^i, α_2^i have the expected signs, except for the featureless types, where the coefficient is slightly negative, but insignificant.[5] A higher fundamental value and a higher last period price both increase the willingness to pay. An F-test rejects the null hypothesis, that both coefficients are the same for all possible combinations of types[6], except for the comparison of TE vs. SO types and TE vs. SE. Further the coefficients for the fundamental value is larger for the technocratic type than for the semiotic, while the latter puts more emphasis on the momentum component, which gives support for H 2.3. Moreover the difference among sophisticated and technocratic types are in line to what we expected, the technocrat has a larger weight on the fundamental price than the sophisticated-type and a lower one on the price of the last period. In table B.5 we test for the differences of the parameters among types. The results suggest, that there are nor significant differences in the coefficients for all typwise comparisons. Beside the coefficients of the fundamental in comparison of the featureless type against the technocratic or sophisticated types.

[5] The Breusch-Pagan test suggests a random-effects model.

[6] At the 5% level for the comparison of the FL vs. SE and at the 10% for the pairs: FL vs. TE, FL vs. SO, SE vs. SO. The same holds if we include the additional requirement of a common intercept.

Table B.5: Comparison of types - Willingness to accept

	FL vs. i=SE	FL vs. i=TE	FL vs. i=SO	SE vs. i=TE	SE vs. i=SO	TE vs. i=SO
FV_t	-0.084	-0.015	-0.084	0.215*	0.255***	0.805**
	(0.2)	(0.2)	(0.2)	(0.116)	(0.097)	(0.417)
p_{t-1}	0.621	0.482	0.621	1.20***	1.17***	0.922***
	(0.432)	(0.517)	(0.432)	(0.358)	(0.291)	(0.185)
d_i*FV_t	0.339	0.817**	0.439**	0.583	0.1	-0.378
	(0.227)	(0.378)	(0.217)	(0.424)	(0.139)	(0.426)
d_i*p_{t-1}	0.551	0.45	0.661	-0.261	0.11	0.24
	(0.505)	(0.542)	(0.423)	(0.453)	(0.342)	(0.189)
d_i	-222.101	-48.07	-347.3**	214	-125.2	-300.49
	(192.65)	(288.57)	(163.74)	(236.04)	(115.68)	(200.57)
Constant	207.773	232.62	207.77	-24.16	-14.33	189.21
	(171.13)	(202.65)	(171.2)	(111.24)	(93.42)	(198.28)
R^2-overall	0.0175	0.0026	0.282	0.031	0.039	0.0034
Observations	1426	1221	1527	1035	1009	804

Standard random effects estimator, using clustered standard errors at the market level, robust standard errors in parentheses. Unit of observation: participant. Data from both groups under consideration is pooled for the specific regression.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: Willingness to pay for each period
Independent variables: "FV:" Fundamental Value, expected dividend earnings at the beginning of the period (, i.e. $FV_t = (16 - t) * 24$; "p_{t-1}:" Price in the last period. "d_i:" Dummy for i-type; $d_i = 1$ if participant is of type i, zero otherwise..

B.11.1 Cash overtime per cognitive type

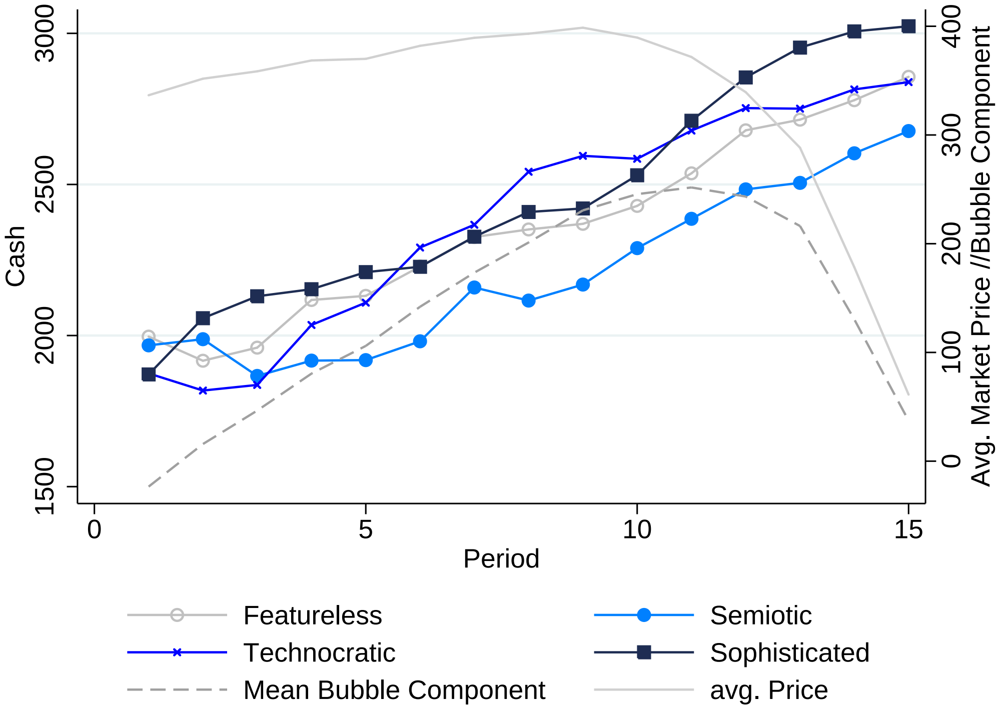


Figure B.21: Cash over time per cognitive type

This figure shows on the left y-axis the average cash holdings per cognitive type. In order to compare market dynamics the average market price (grey line) and the average bubble component (, i.e. market price less expected value of the asset) (grey dotted line) are added on the right y-axis. As one can see, the difference between the sophisticated types and the rest, comes from selling the asset before the price starts do decline steeply.

B.11.2 Type distribution and market outcome

Figure B.22 reports the number of cognitive types in each market. The baseline markets 1-16 were all similar and the treatment markets, differed, with the markets 1-6 are the low-markets and 7-12 are the high ones. While the baseline treatment show a fairly even distribution of types, the segregation treatments show the intended unbalanced distribution of types. This approves ex-post the chosen segregation procedure.

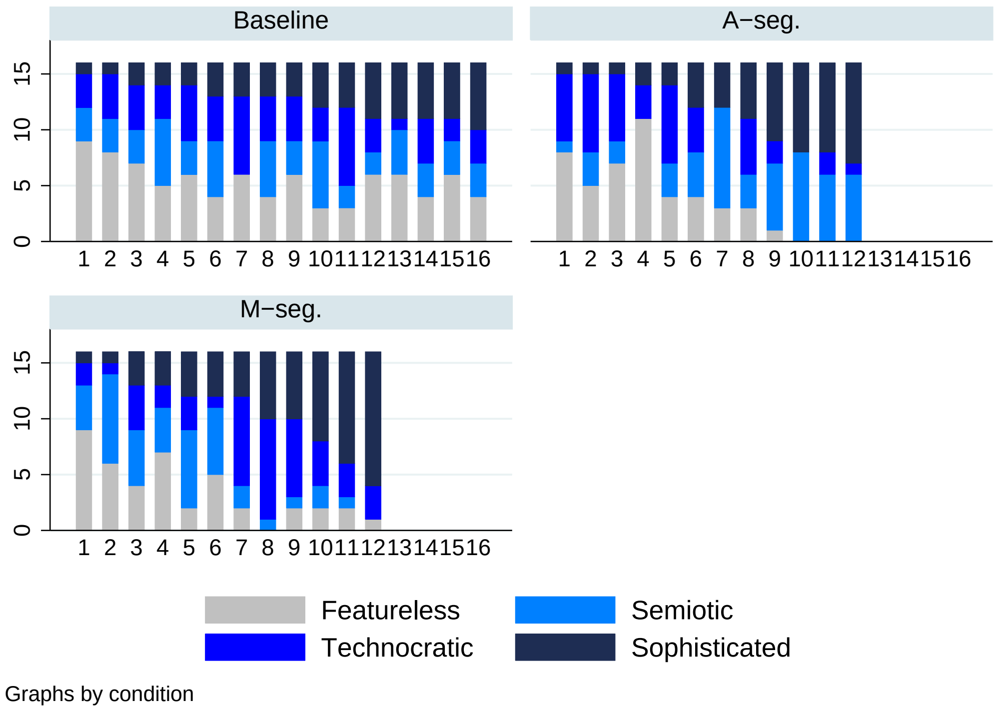


Figure B.22: Distribution of cognitive types across the markets

These figures show the type distribution in each of the 42 markets of the experiment. The baseline markets show a fairly even distribution of types, the additional markets, where the markets 1-6 are the low-markets and 7-12 are the high ones. Thus the separation worked.

C Appendix: Chapter 3

C.1 Correlation among measures

Table C.1: Summary Statistics

	AN	CE	# Risky Choices	risk1	risk2	risk3	risk4	riks5	risk6	risk8	OCrel	p-stockmarket	# Stock Traded	patience	impulsiveness	age	gender
AN	1.00																
CE	0.10	1.00															
# Risky Choices	0.12***	0.01	1.00														
risk1	-0.04	-0.01	0.17***	1.00													
risk2	0.04	-0.05	0.07	0.17***	1.00												
risk3	-0.01	-0.028	0.12***	0.48***	0.36***	1.00											
risk4	0.03	0.01	0.14***	0.35***	0.23***	0.25***	1.00										
risk5	-0.02	-0.03	0.11***	0.40***	0.21***	0.39***	0.40***	1.00									
risk6	0.05	0.02	0.10	0.21***	0.36***	0.19***	0.29***	0.23***	1.00								
risk8	0.07	0.04	0.14***	0.25***	0.15***	0.28***	0.08	0.1	0.07	1.00							
OCrel	-0.34***	-0.0007	0.07	0.04	0.05	0.06	0.02	0.06	-0.04	-0.007	1.00						
p-stockmarket	0.04	0.08	0.06	0.09	0.07	0.20***	0.05	0.09	0.01	0.06	0.07	1.00					
# Stock Traded	-0.10***	0.01	0.05	0.06	-0.04	0.07	-0.003	0.01	-0.07	0.02	0.07	0.20	1.00				
patience	0.10	-0.10	0.06	-0.0007	-0.15***	0.009	-0.05	0.03	-0.07	0.02	-0.01	0.01	0.002	1.00			
impulsiveness	-0.15***	-0.02	-0.02	0.30***	0.08	0.17***	0.12***	0.15***	0.12***	0.03	0.04	-0.06	0.01	-0.26***	1.00		
age	-0.14***	-0.02	-0.04	-0.02	0.02	0.03	0.004	0.16***	-0.09	-0.08	0.12***	0.014	-0.02	0.10	-0.001	1.00	
gender	-0.29***	0.08	-0.20***	-0.15***	-0.13***	-0.19***	-0.15***	-0.014***	-0.07	-0.12***	-0.07	-0.20***	0.01	-0.18***	0.19***	-0.07	1.00

"***": Significance level $p<0.01$. N=640, *# Risky Choices, OCrel, risk1-risk8, p-stockmarket, # Stock Traded, patience, impulsivness* and *gender* are as described above in section 2.4. *AN* and *CE* are the two mental capacities as described in chapter 2.

C.2 Trading Behavior

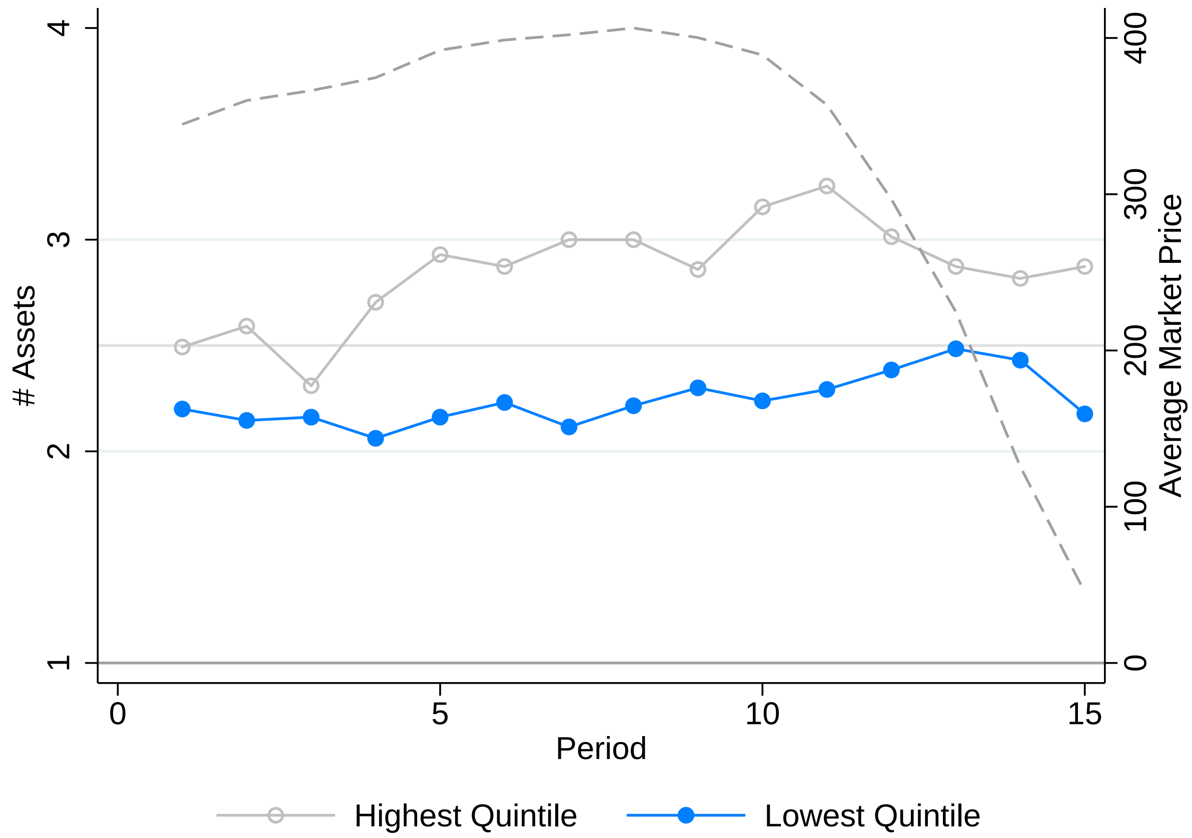
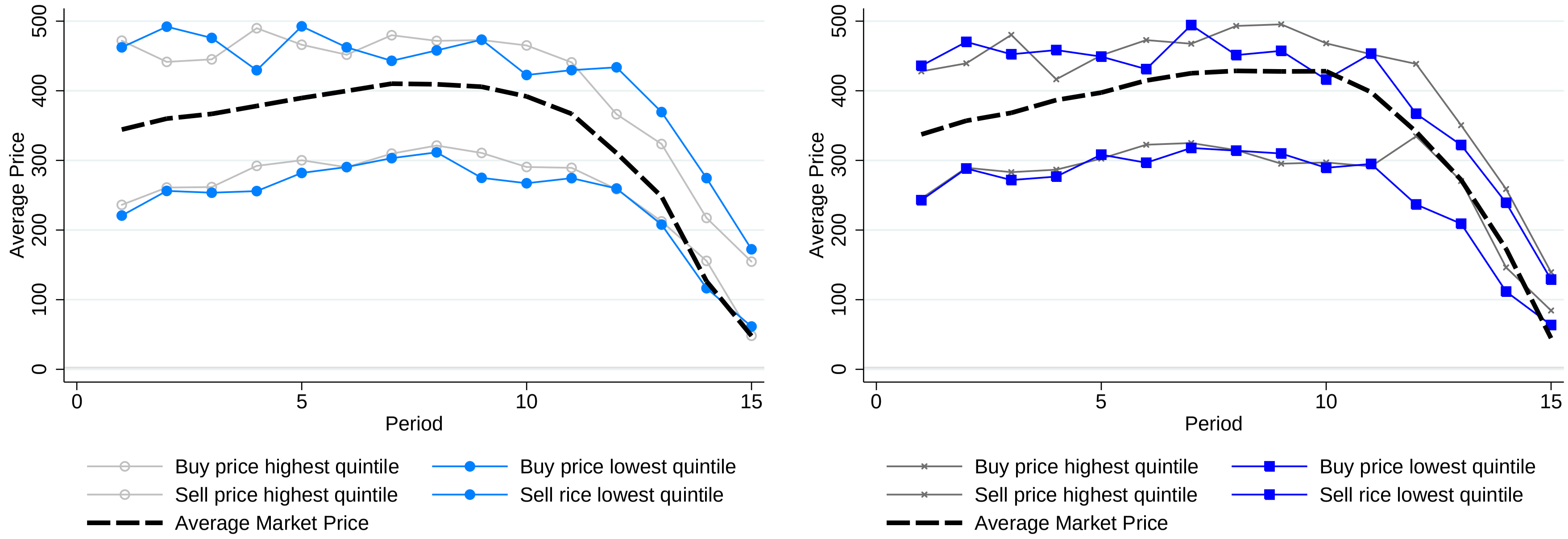


Figure C.1: Mean asset holdings (Risk)

This graph plots the average market price (dashed line), mean asset holdings for the highest and lowest quintile in terms of # Risky Choices (Holt-Laury-Task). The highest (lowest) quintile is the group of the 20% of participants who choose the highest (lowest) risky number before switching to the certain payout and thus can be interpreted as the least (most) risk averse group. Since participants could either hold cash or assets in their portfolio, a higher number of assets can be interpreted also as choosing a riskier portfolio.



(a) Risky Choices

(b) Relative Over-Confidence

Figure C.2: Buy and Sell Prices of the highest and lowest quintile

This graph plots the average market price (dashed line), mean buy order prices (lines below the average market price) and mean sell order prices (lines above the market prices) for the highest and lowest quintile in the risk- (a) and relative overconfidence (b) measures. Sell orders above 2000 Rappen and buy orders at zero are classified as not serious orders.

C.2.1 All Periods

Table C.2: Regression analysis offered buy prices, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.38			
	[-1.28,2.03]			
OCrel		3.14		
		[-1.39,7.66]		
risk3			2.25	
			[-0.68,5.19]	
risk5				1.86*
				[-0.29,4.00]
Age	-0.98	-1.16	-1.01	-1.20
	[-3.27,1.30]	[-3.49,1.16]	[-3.32,1.30]	[-3.51,1.10]
Gender	15.12**	15.08**	16.40**	15.69**
	[0.60,29.63]	[0.99,29.17]	[1.86,30.93]	[1.87,29.51]
Constant	260.62***	266.49***	258.49***	260.81***
	[195.74,325.50]	[208.34,324.63]	[199.39,317.58]	[204.25,317.37]
R-squared	0.004	0.005	0.005	0.005
N	7811	7811	7811	7811

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Buy Price:” Offered buy prices, in Rappen.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.3: Regression analysis offered sell prices, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	27.39			
	[-15.59,70.37]			
OCrel		19.00		
		[-112.11,150.11]		
risk3			15.91	
			[-77.96,109.79]	
risk5				47.62
				[-38.01,133.25]
Age	46.12	43.30	44.26	39.50
	[-21.35,113.60]	[-25.53,112.12]	[-22.81,111.33]	[-32.85,111.85]
Gender	-96.41	-129.73	-120.23	-105.29
	[-459.18,266.37]	[-505.80,246.34]	[-516.82,276.36]	[-482.58,272.00]
Constant	-733.35	-346.40	-402.54	-487.74
	[-2316.81,850.10]	[-1655.69,962.89]	[-1810.79,1005.71]	[-1796.67,821.19]
R-squared	0.003	0.002	0.002	0.003
N	6303	6303	6303	6303

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Sell Price:" Offered sell prices, in Rappen.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.4: Regression analysis offered buy volume, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	-0.57			
	[-2.20,1.05]			
OCrel		-1.39		
		[-4.74,1.95]		
risk3			-0.78	
			[-2.41,0.84]	
risk5				-0.56
				[-2.86,1.74]
Age	0.31	0.41	0.34	0.40
	[-0.44,1.06]	[-0.35,1.17]	[-0.41,1.09]	[-0.35,1.15]
Gender	-18.17***	-17.50***	-17.90***	-17.60***
	[-29.56,-6.78]	[-28.37,-6.63]	[-28.94,-6.86]	[-28.65,-6.56]
Constant	23.11*	14.94*	17.79*	16.75
	[-1.52,47.75]	[-2.50,32.38]	[-1.08,36.66]	[-3.79,37.29]
R-squared	0.003	0.003	0.003	0.003
N	7811	7811	7811	7811

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Buy Volume:” Offered numbers of assets to buy.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.5: Regression analysis offered sell volume, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.05***			
	[0.02,0.08]			
OCrel		-0.06		
		[-0.16,0.04]		
risk3			0.03	
			[-0.02,0.09]	
risk5				0.01
				[-0.03,0.06]
Age	-0.01	-0.01	-0.02	-0.02
	[-0.04,0.02]	[-0.05,0.02]	[-0.05,0.02]	[-0.05,0.01]
Gender	-0.65***	-0.73***	-0.68***	-0.70***
	[-0.86,-0.43]	[-0.93,-0.52]	[-0.90,-0.47]	[-0.91,-0.49]
Constant	2.31***	2.98***	2.86***	2.93***
	[1.42,3.21]	[2.19,3.77]	[2.06,3.65]	[2.16,3.71]
R-squared	0.038	0.033	0.032	0.031
N	6303	6303	6303	6303

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Sell Volume:" Offered numbers of assets to sell.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.6: Regression analysis Assets hold, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.02			
	[-0.02,0.06]			
OCrel		-0.00		
		[-0.11,0.11]		
risk3			0.07**	
			[0.00,0.14]	
risk5				0.04
				[-0.02,0.10]
Age	-0.01	-0.01	-0.01	-0.02
	[-0.06,0.04]	[-0.07,0.04]	[-0.07,0.04]	[-0.07,0.04]
Gender	-0.04	-0.08	-0.02	-0.06
	[-0.41,0.32]	[-0.42,0.25]	[-0.36,0.31]	[-0.39,0.28]
Constant	2.49***	2.82***	2.60***	2.72***
	[1.17,3.82]	[1.57,4.08]	[1.36,3.85]	[1.46,3.98]
R-squared	0.001	0.000	0.003	0.002
N	9600	9600	9600	9600

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Assets:" Assets hold at the end of the period.
Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.7: Regression analysis asset change, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	-0.00			
	[-0.01,0.00]			
OCrel		0.01		
		[-0.01,0.02]		
risk3			0.01**	
			[0.00,0.02]	
risk5				0.01*
				[-0.00,0.01]
Age	-0.00	-0.00	-0.00	-0.00
	[-0.01,0.01]	[-0.01,0.01]	[-0.01,0.01]	[-0.01,0.00]
Gender	0.01	0.01	0.02	0.02
	[-0.04,0.06]	[-0.04,0.06]	[-0.03,0.07]	[-0.03,0.06]
Constant	0.03	0.02	-0.01	0.01
	[-0.14,0.21]	[-0.14,0.19]	[-0.17,0.14]	[-0.15,0.17]
R-squared	0.000	0.000	0.000	0.000
N	9600	9600	9600	9600

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Asset change:" Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.8: Regression participation, all Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.003			
	[-0.002,0.007]			
OCrel		0.005		
		[-0.005,0.015]		
risk3			0.006*	
			[-0.001,0.012]	
risk5				0.005*
				[-0.001,0.010]
Age	-0.000	-0.001	-0.000	-0.001
	[-0.003,0.003]	[-0.004,0.003]	[-0.004,0.003]	[-0.004,0.003]
Gender	0.008	0.005	0.008	0.007
	[-0.017,0.033]	[-0.019,0.028]	[-0.015,0.031]	[-0.016,0.029]
Constant	0.885***	0.921***	0.903***	0.909***
	[0.797,0.973]	[0.849,0.994]	[0.825,0.981]	[0.833,0.984]
R-squared	0.001	0.001	0.002	0.002
N	9600	9600	9600	9600

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Dependent variable: “Asset change:” Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

C.2.2 1st Period

Table C.9: Regression analysis offered buy prices, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	-0.14			
	[-2.70,2.42]			
OCrel		-3.25		
		[-11.50,5.00]		
risk3			-1.62	
			[-6.30,3.06]	
risk5				0.08
				[-3.15,3.30]
Age	1.58	1.75	1.60	1.58
	[-2.38,5.55]	[-2.18,5.68]	[-2.33,5.53]	[-2.40,5.57]
Gender	-47.80***	-48.12***	-49.00***	-47.54***
	[-68.15,-27.46]	[-67.64,-28.60]	[-67.69,-30.31]	[-66.78,-28.30]
Constant	235.18***	232.78***	238.49***	233.07***
	[128.01,342.35]	[138.17,327.39]	[146.87,330.12]	[138.10,328.04]
R-squared	0.043	0.044	0.044	0.043
N	627	627	627	627

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: “Buy Price:” Offered buy prices, in Rappen.
Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.10: Regression analysis offered sell prices, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	-2.24			
	[-8.78,4.31]			
OCrel		-2.62		
		[-15.74,10.49]		
risk3			-5.26	
			[-14.57,4.06]	
risk5				-3.54
				[-11.59,4.51]
Age	3.32	3.59	3.52	3.87
	[-3.08,9.73]	[-3.18,10.36]	[-2.98,10.02]	[-2.68,10.41]
Gender	-48.84**	-45.85**	-49.55**	-47.35**
	[-96.38,-1.30]	[-89.44,-2.27]	[-96.40,-2.70]	[-93.83,-0.86]
Constant	419.50***	387.57***	403.93***	396.88***
	[252.73,586.27]	[225.79,549.36]	[250.23,557.62]	[233.55,560.21]
R-squared	0.011	0.010	0.012	0.011
N	575	575	575	575

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Price:” Offered sell prices, in Rappen.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.11: Regression analysis offered buy volume, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	-1.17			
	[-3.59,1.24]			
OCrel		1.10		
		[-0.53,2.74]		
risk3			1.64*	
			[-0.23,3.51]	
risk5				0.28
				[-0.25,0.81]
Age	0.06	0.07	0.11	0.09
	[-0.60,0.71]	[-0.73,0.87]	[-0.64,0.87]	[-0.72,0.91]
Gender	-8.22	-6.24	-4.99	-6.23
	[-21.23,4.80]	[-15.82,3.35]	[-13.28,3.29]	[-15.99,3.54]
Constant	24.67	8.57	3.11	7.66
	[-8.31,57.66]	[-6.73,23.87]	[-12.60,18.82]	[-7.15,22.47]
R-squared	0.009	0.004	0.007	0.003
N	627	627	627	627

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Buy Volume:" Offered numbers of assets to buy.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.12: Regression analysis offered sell volume, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.01			
	[-0.01,0.03]			
OCrel		-0.03		
		[-0.09,0.02]		
risk3			0.00	
			[-0.03,0.04]	
risk5				0.02
				[-0.01,0.05]
Age	0.01	0.01	0.00	0.00
	[-0.01,0.02]	[-0.01,0.02]	[-0.01,0.02]	[-0.02,0.02]
Gender	-0.25***	-0.27***	-0.26***	-0.26***
	[-0.39,-0.10]	[-0.42,-0.13]	[-0.41,-0.12]	[-0.40,-0.12]
Constant	1.67***	1.82***	1.82***	1.78***
	[1.11,2.23]	[1.36,2.27]	[1.37,2.26]	[1.34,2.22]
R-squared	0.023	0.024	0.021	0.024
N	575	575	575	575

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Volume:” Offered numbers of assets to sell.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.13: Regression analysis Assets hold, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.02			
	[-0.01,0.05]			
OCrel		0.03		
		[-0.09,0.15]		
risk3			-0.01	
			[-0.08,0.06]	
risk5				-0.02
				[-0.07,0.03]
Age	0.02	0.02	0.02	0.02
	[-0.02,0.06]	[-0.02,0.05]	[-0.02,0.06]	[-0.02,0.06]
Gender	-0.64***	-0.67***	-0.68***	-0.69***
	[-0.94,-0.34]	[-0.96,-0.38]	[-0.97,-0.39]	[-0.98,-0.40]
Constant	2.11***	2.40***	2.42***	2.45***
	[1.04,3.17]	[1.51,3.29]	[1.49,3.35]	[1.57,3.33]
R-squared	0.040	0.038	0.038	0.038
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Dependent variable: “Assets:” Assets hold at the end of the period.
Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.14: Regression analysis asset change, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.01			
	[-0.02,0.04]			
OCrel		0.06		
		[-0.05,0.18]		
risk3			-0.02	
			[-0.09,0.04]	
risk5				-0.02
				[-0.07,0.02]
Age	0.00	-0.00	0.00	0.00
	[-0.04,0.04]	[-0.04,0.04]	[-0.04,0.04]	[-0.04,0.04]
Gender	-0.68***	-0.68***	-0.71***	-0.70***
	[-0.95,-0.40]	[-0.95,-0.41]	[-0.98,-0.44]	[-0.97,-0.43]
Constant	0.22	0.32	0.39	0.37
	[-0.90,1.34]	[-0.64,1.28]	[-0.60,1.37]	[-0.57,1.31]
R-squared	0.039	0.041	0.039	0.040
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Asset change:" Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.15: Regression participation, 1st Periods

	(1)	(2)	(3)	(4)
# Risky Choices	0.001			
	[-0.001,0.002]			
OCrel		-0.001		
		[-0.005,0.004]		
risk3			0.000	
			[-0.004,0.005]	
risk5				0.001
				[-0.002,0.004]
Age	0.000	0.000	0.000	0.000
	[-0.000,0.001]	[-0.000,0.001]	[-0.000,0.001]	[-0.001,0.001]
Gender	-0.005	-0.006	-0.006	-0.005
	[-0.016,0.006]	[-0.019,0.006]	[-0.020,0.008]	[-0.018,0.007]
Constant	0.978***	0.987***	0.986***	0.984***
	[0.950,1.007]	[0.964,1.010]	[0.959,1.014]	[0.959,1.008]
R-squared	0.003	0.002	0.002	0.004
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Asset change:” Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

C.2.3 Before Bubble Peak

Table C.16: Regression analysis offered buy prices, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.84			
	[-0.76,2.44]			
OCrel		2.68		
		[-1.94,7.30]		
risk3			1.88	
			[-0.95,4.72]	
risk5				1.80*
				[-0.28,3.88]
Age	-1.50	-1.68	-1.55	-1.74
	[-3.61,0.61]	[-3.83,0.48]	[-3.69,0.60]	[-3.86,0.37]
Gender	3.59	2.78	4.01	3.57
	[-9.78,16.96]	[-10.06,15.62]	[-9.21,17.23]	[-8.94,16.09]
Constant	301.96***	314.04***	307.25***	308.72***
	[243.51,360.42]	[261.57,366.50]	[254.06,360.44]	[257.33,360.12]
R-squared	0.003	0.003	0.003	0.004
N	6162	6162	6162	6162

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: “Buy Price:” Offered buy prices, in Rappen.
Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.17: Regression analysis offered sell prices, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	21.51			
	[-16.69,59.71]			
OCrel		-24.58		
		[-116.93,67.77]		
risk3			-12.60	
			[-94.90,69.70]	
risk5				27.62
				[-28.40,83.65]
Age	54.11	54.11	52.89	50.10
	[-34.07,142.28]	[-35.21,143.44]	[-34.29,140.08]	[-41.58,141.79]
Gender	-229.77	-266.07	-272.34	-241.79
	[-621.65,162.11]	[-694.42,162.28]	[-707.83,163.15]	[-665.13,181.55]
Constant	-733.80	-438.66	-393.18	-516.99
	[-2769.40,1301.81]	[-2150.98,1273.66]	[-2224.08,1437.71]	[-2184.39,1150.41]
R-squared	0.004	0.004	0.004	0.004
N	4642	4642	4642	4642

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Price:” Offered sell prices, in Rappen.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.18: Regression analysis offered buy volume, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.03			
	[-0.97,1.03]			
OCrel		-2.38		
		[-5.65,0.88]		
risk3			-0.60	
			[-2.59,1.39]	
risk5				-1.22
				[-3.14,0.70]
Age	0.07	0.19	0.07	0.21
	[-0.44,0.59]	[-0.41,0.79]	[-0.45,0.60]	[-0.38,0.79]
Gender	-9.43**	-9.94**	-10.03*	-10.37*
	[-18.04,-0.81]	[-19.60,-0.29]	[-20.12,0.06]	[-20.77,0.04]
Constant	12.82*	12.74*	15.20*	16.45*
	[-2.08,27.72]	[-0.73,26.21]	[-2.96,33.35]	[-0.14,33.04]
R-squared	0.001	0.002	0.001	0.001
N	6162	6162	6162	6162

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Buy Volume:” Offered numbers of assets to buy.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.19: Regression analysis offered sell volume, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.03***			
	[0.01,0.05]			
OCrel		-0.03		
		[-0.10,0.05]		
risk3			0.03	
			[-0.03,0.08]	
risk5				-0.00
				[-0.04,0.04]
Age	-0.00	-0.00	-0.00	-0.00
	[-0.03,0.02]	[-0.03,0.02]	[-0.03,0.02]	[-0.03,0.02]
Gender	-0.59***	-0.64***	-0.61***	-0.64***
	[-0.78,-0.40]	[-0.83,-0.46]	[-0.80,-0.43]	[-0.82,-0.45]
Constant	1.92***	2.36***	2.27***	2.36***
	[1.15,2.68]	[1.67,3.04]	[1.61,2.93]	[1.68,3.04]
R-squared	0.040	0.035	0.036	0.035
N	4642	4642	4642	4642

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Sell Volume:" Offered numbers of assets to sell.
Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.20: Regression analysis Assets hold, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.03			
	[-0.01,0.07]			
OCrel		0.01		
		[-0.10,0.12]		
risk3			0.03	
			[-0.03,0.10]	
risk5				0.02
				[-0.04,0.08]
Age	-0.00	-0.00	-0.00	-0.00
	[-0.05,0.05]	[-0.05,0.05]	[-0.05,0.05]	[-0.05,0.04]
Gender	-0.15	-0.19	-0.16	-0.18
	[-0.51,0.22]	[-0.53,0.14]	[-0.49,0.16]	[-0.51,0.15]
Constant	2.24***	2.64***	2.53***	2.59***
	[0.98,3.51]	[1.48,3.80]	[1.38,3.68]	[1.44,3.74]
R-squared	0.003	0.001	0.002	0.002
N	6880	6880	6880	6880

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Assets:” Assets hold at the end of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.21: Regression analysis asset change, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.00			
	[-0.00,0.01]			
OCrel		0.00		
		[-0.02,0.02]		
risk3			0.01	
			[-0.00,0.02]	
risk5				0.00
				[-0.00,0.01]
Age	-0.00	-0.00	-0.00	-0.00
	[-0.01,0.01]	[-0.01,0.01]	[-0.01,0.01]	[-0.01,0.01]
Gender	0.01	0.00	0.01	0.01
	[-0.04,0.06]	[-0.05,0.06]	[-0.04,0.06]	[-0.04,0.06]
Constant	-0.01	0.03	0.01	0.02
	[-0.22,0.20]	[-0.16,0.22]	[-0.17,0.19]	[-0.17,0.21]
R-squared	0.000	0.000	0.000	0.000
N	6880	6880	6880	6880

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Asset change:” Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.22: Regression participation, before bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.002			
	[-0.001,0.006]			
OCrel		0.003		
		[-0.006,0.012]		
risk3			0.002	
			[-0.003,0.008]	
risk5				0.005**
				[0.000,0.011]
Age	-0.001	-0.001	-0.001	-0.002
	[-0.003,0.002]	[-0.004,0.001]	[-0.004,0.001]	[-0.004,0.001]
Gender	-0.010	-0.014	-0.012	-0.010
	[-0.029,0.008]	[-0.032,0.005]	[-0.031,0.007]	[-0.028,0.008]
Constant	0.948***	0.979***	0.971***	0.965***
	[0.877,1.018]	[0.924,1.034]	[0.909,1.032]	[0.908,1.022]
R-squared	0.003	0.001	0.002	0.005
N	6880	6880	6880	6880

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Asset change:” Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

C.2.4 After Bubble Peak

Table C.23: Regression analysis offered buy prices, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	-1.85*			
	[-4.05,0.36]			
OCrel		5.57		
		[-2.16,13.30]		
risk3			2.04	
			[-1.87,5.95]	
risk5				2.78
				[-1.12,6.68]
Age	0.39	0.14	0.44	0.17
	[-3.28,4.05]	[-3.66,3.94]	[-3.30,4.18]	[-3.58,3.93]
Gender	37.58***	41.42***	41.73***	41.49***
	[16.05,59.12]	[20.22,62.62]	[20.98,62.49]	[20.12,62.86]
Constant	136.49***	113.42**	105.49**	103.86**
	[47.80,225.18]	[23.17,203.68]	[14.35,196.63]	[15.35,192.36]
R-squared	0.025	0.026	0.024	0.026
N	1649	1649	1649	1649

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Buy Price:" Offered buy prices, in Rappen.
Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.24: Regression analysis offered sell prices, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	38.51			
	[-39.73,116.75]			
OCrel		143.72		
		[-136.38,423.82]		
risk3			89.83	
			[-76.11,255.78]	
risk5				100.70
				[-90.22,291.62]
Age	21.85*	11.40	17.95	8.33
	[-3.27,46.97]	[-22.90,45.71]	[-7.55,43.44]	[-26.98,43.63]
Gender	287.37	274.68	301.54	280.69
	[-204.67,779.42]	[-199.23,748.59]	[-195.35,798.43]	[-179.68,741.07]
Constant	-654.30	-95.24	-388.94	-386.84
	[-1784.04,475.44]	[-746.61,556.14]	[-1062.66,284.77]	[-1072.58,298.90]
R-squared	0.003	0.004	0.004	0.007
N	1661	1661	1661	1661

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Price:” Offered sell prices, in Rappen.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.25: Regression analysis offered buy volume, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	-2.80			
	[-9.39,3.80]			
OCrel		2.46		
		[-9.28,14.19]		
risk3			-0.70	
			[-4.18,2.79]	
risk5				2.31
				[-5.17,9.79]
Age	1.41	1.38	1.53	1.29
	[-1.77,4.60]	[-2.18,4.94]	[-1.73,4.79]	[-1.77,4.34]
Gender	-48.58**	-43.49**	-44.11**	-43.17**
	[-90.54,-6.63]	[-76.68,-10.29]	[-77.58,-10.63]	[-75.46,-10.88]
Constant	53.86	16.90	18.10	9.72
	[-25.25,132.97]	[-51.40,85.21]	[-48.40,84.60]	[-62.88,82.32]
R-squared	0.009	0.008	0.008	0.008
N	1649	1649	1649	1649

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Buy Volume:” Offered numbers of assets to buy.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.26: Regression analysis offered sell volume, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.09***			
	[0.03,0.15]			
OCrel		-0.18*		
		[-0.40,0.03]		
risk3			0.05	
			[-0.05,0.15]	
risk5				0.06
				[-0.03,0.14]
Age	-0.03	-0.04	-0.05	-0.05
	[-0.09,0.02]	[-0.10,0.02]	[-0.11,0.02]	[-0.11,0.01]
Gender	-0.98***	-1.13***	-1.06***	-1.07***
	[-1.42,-0.55]	[-1.54,-0.72]	[-1.48,-0.63]	[-1.48,-0.66]
Constant	3.26***	4.65***	4.44***	4.44***
	[1.50,5.02]	[3.19,6.11]	[2.96,5.92]	[2.98,5.89]
R-squared	0.059	0.052	0.044	0.046
N	1661	1661	1661	1661

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: “Sell Volume:” Offered numbers of assets to sell.
Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.27: Regression analysis Assets hold, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.01			
	[-0.06,0.08]			
OCrel		-0.02		
		[-0.19,0.14]		
risk3			0.16***	
			[0.05,0.26]	
risk5				0.09**
				[0.00,0.18]
Age	-0.04	-0.04	-0.04	-0.05
	[-0.12,0.04]	[-0.12,0.04]	[-0.12,0.04]	[-0.13,0.03]
Gender	0.21	0.19	0.30	0.24
	[-0.32,0.75]	[-0.31,0.70]	[-0.19,0.78]	[-0.25,0.74]
Constant	3.15***	3.31***	2.87***	3.07***
	[1.12,5.19]	[1.45,5.17]	[1.01,4.72]	[1.18,4.97]
R-squared	0.003	0.003	0.013	0.008
N	2720	2720	2720	2720

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Assets:” Assets hold at the end of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.28: Regression analysis asset change, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	-0.01			
	[-0.02,0.00]			
OCrel		0.02		
		[-0.02,0.07]		
risk3			0.02**	
			[0.00,0.05]	
risk5				0.01
				[-0.01,0.03]
Age	-0.00	-0.00	-0.00	-0.00
	[-0.02,0.01]	[-0.02,0.01]	[-0.02,0.01]	[-0.02,0.01]
Gender	0.01	0.03	0.04	0.03
	[-0.12,0.14]	[-0.09,0.16]	[-0.08,0.16]	[-0.09,0.15]
Constant	0.14	0.00	-0.07	-0.03
	[-0.31,0.60]	[-0.37,0.38]	[-0.44,0.31]	[-0.40,0.34]
R-squared	0.001	0.000	0.001	0.000
N	2720	2720	2720	2720

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Asset change:" Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.29: Regression participation, after bubble peake

	(1)	(2)	(3)	(4)
# Risky Choices	0.003			
	[-0.005,0.011]			
OCrel		0.010		
		[-0.008,0.028]		
risk3			0.012**	
			[0.001,0.024]	
risk5				0.003
				[-0.006,0.012]
Age	0.001	0.000	0.001	0.000
	[-0.006,0.008]	[-0.007,0.007]	[-0.006,0.008]	[-0.006,0.007]
Gender	0.047*	0.043*	0.049**	0.043*
	[-0.004,0.097]	[-0.003,0.090]	[0.004,0.095]	[-0.003,0.089]
Constant	0.749***	0.798***	0.761***	0.789***
	[0.568,0.929]	[0.643,0.952]	[0.596,0.926]	[0.629,0.948]
R-squared	0.004	0.005	0.008	0.003
N	2720	2720	2720	2720

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Dependent variable: “Asset change:” Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

C.2.5 15th Period

Table C.30: Regression analysis offered buy prices, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	-1.65*			
	[-3.56,0.27]			
OCrel		-0.27		
		[-5.15,4.61]		
risk3			0.86	
			[-2.35,4.06]	
risk5				-0.06
				[-2.97,2.86]
Age	1.32	1.40	1.36	1.40
	[-1.05,3.70]	[-1.04,3.85]	[-1.09,3.81]	[-1.00,3.80]
Gender	27.20**	29.98***	30.40***	30.00**
	[5.27,49.13]	[7.84,52.12]	[8.49,52.31]	[7.43,52.56]
Constant	19.77	-2.43	-4.51	-2.32
	[-38.73,78.26]	[-60.43,55.56]	[-64.50,55.47]	[-61.94,57.29]
R-squared	0.067	0.059	0.060	0.059
N	333	333	333	333

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Buy Price:" Offered buy prices, in Rappen.
Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.31: Regression analysis offered sell prices, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	-11.91			
	[-50.72,26.90]			
OCrel		-8.09		
		[-32.38,16.21]		
risk3			32.08	
			[-22.19,86.35]	
risk5				9.60
				[-5.72,24.92]
Age	30.26	31.34	31.83	30.12
	[-14.39,74.92]	[-12.60,75.27]	[-10.40,74.06]	[-12.90,73.15]
Gender	31.72	44.35	74.78	51.24
	[-217.69,281.13]	[-161.94,250.65]	[-93.15,242.71]	[-153.91,256.39]
Constant	-355.28	-517.84	-651.15	-548.15
	[-1855.15,1144.58]	[-1597.66,561.99]	[-1634.21,331.90]	[-1619.54,523.24]
R-squared	0.022	0.019	0.026	0.020
N	354	354	354	354

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Price:” Offered sell prices, in Rappen.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.32: Regression analysis offered buy volume, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	-4.01			
	[-21.42,13.40]			
OCrel		15.24		
		[-19.05,49.52]		
risk3			-6.08	
			[-17.91,5.75]	
risk5				3.10
				[-11.57,17.77]
Age	5.85	5.39	6.23	5.61
	[-1.45,13.16]	[-3.51,14.29]	[-1.73,14.20]	[-1.68,12.89]
Gender	-109.85**	-101.19**	-105.69**	-101.86**
	[-206.14,-13.56]	[-179.87,-22.51]	[-188.83,-22.56]	[-181.47,-22.25]
Constant	25.27	-28.54	-14.03	-34.92
	[-132.50,183.05]	[-191.96,134.88]	[-183.02,154.96]	[-209.06,139.23]
R-squared	0.019	0.021	0.019	0.018
N	333	333	333	333

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Buy Volume:” Offered numbers of assets to buy.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.33: Regression analysis offered sell volume, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	0.06			
	[-0.02,0.14]			
OCrel		0.01		
		[-0.25,0.27]		
risk3			0.00	
			[-0.14,0.14]	
risk5				-0.00
				[-0.15,0.14]
Age	-0.05	-0.05	-0.05	-0.05
	[-0.13,0.04]	[-0.13,0.04]	[-0.13,0.03]	[-0.13,0.04]
Gender	-1.28***	-1.35***	-1.35***	-1.35***
	[-2.02,-0.54]	[-2.07,-0.62]	[-2.12,-0.58]	[-2.11,-0.59]
Constant	4.61***	5.41***	5.41***	5.42***
	[2.25,6.96]	[3.20,7.62]	[3.16,7.66]	[3.15,7.70]
R-squared	0.049	0.044	0.044	0.044
N	354	354	354	354

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Sell Volume:” Offered numbers of assets to sell.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.34: Regression analysis Assets hold, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	0.00			
	[-0.07,0.08]			
OCrel		0.08		
		[-0.11,0.26]		
risk3			0.20***	
			[0.08,0.31]	
risk5				0.11*
				[-0.00,0.22]
Age	-0.00	-0.00	-0.00	-0.01
	[-0.10,0.10]	[-0.11,0.10]	[-0.11,0.10]	[-0.11,0.09]
Gender	0.18	0.19	0.34	0.25
	[-0.58,0.95]	[-0.53,0.91]	[-0.35,1.04]	[-0.47,0.96]
Constant	2.38*	2.44**	1.81	2.17*
	[-0.17,4.93]	[0.00,4.89]	[-0.61,4.24]	[-0.26,4.59]
R-squared	0.001	0.001	0.013	0.005
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: “Assets:” Assets hold at the end of the period.

Independent variables: “# Risky Choices:” Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; “OCrel:” Relative over-confidence measure; ‘risk3:” Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; ‘risk5:” Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; “Age:” Self-reported age of the participant; ‘Gender:” Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.35: Regression analysis asset change, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	-0.00			
	[-0.03,0.03]			
OCrel		0.04		
		[-0.10,0.18]		
risk3			0.06**	
			[0.00,0.11]	
risk5				0.04
				[-0.02,0.09]
Age	0.03*	0.03*	0.03*	0.03
	[-0.00,0.06]	[-0.01,0.06]	[-0.00,0.06]	[-0.01,0.06]
Gender	-0.20	-0.18	-0.14	-0.17
	[-0.48,0.09]	[-0.46,0.09]	[-0.41,0.12]	[-0.43,0.09]
Constant	-0.60	-0.63	-0.81**	-0.72*
	[-1.47,0.28]	[-1.44,0.18]	[-1.60,-0.02]	[-1.51,0.06]
R-squared	0.005	0.006	0.009	0.007
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Asset change:" Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.36: Regression participation, 15th period

	(1)	(2)	(3)	(4)
# Risky Choices	0.002			
	[-0.008,0.011]			
OCrel		0.020		
		[-0.004,0.043]		
risk3			0.019**	
			[0.003,0.035]	
risk5				0.003
				[-0.010,0.016]
Age	-0.000	-0.001	-0.000	-0.000
	[-0.010,0.010]	[-0.011,0.009]	[-0.010,0.010]	[-0.011,0.010]
Gender	0.032	0.033	0.045	0.032
	[-0.047,0.111]	[-0.042,0.108]	[-0.030,0.121]	[-0.044,0.108]
Constant	0.736***	0.759***	0.698***	0.749***
	[0.475,0.996]	[0.521,0.997]	[0.449,0.946]	[0.507,0.990]
R-squared	0.001	0.005	0.010	0.002
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Asset change:" Assets hold at the end of the period less the assets hold at the beginning of the period.

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

Table C.37: Regression analysis cash at the end of period 15th

	(1)	(2)	(3)	(4)
# Risky Choices	6.97			
	[-6.83,20.78]			
OCrel		-28.45		
		[-70.02,13.11]		
risk3			-14.80	
			[-42.84,13.24]	
risk5				-10.48
				[-34.83,13.86]
Age	4.60	5.56	4.31	5.40
	[-11.13,20.33]	[-10.11,21.23]	[-11.40,20.02]	[-10.65,21.45]
Gender	-163.63***	-179.84***	-187.27***	-181.71***
	[-284.26,-42.99]	[-299.30,-60.38]	[-300.08,-74.46]	[-301.29,-62.13]
Constant	2806.85***	2900.53***	2950.34***	2930.46***
	[2386.45,3227.26]	[2520.29,3280.76]	[2583.26,3317.41]	[2556.85,3304.07]
R-squared	0.016	0.017	0.017	0.016
N	640	640	640	640

OLS regressions, 95% confidence intervals in parentheses, adjusted for clustering at the market level, using White sandwich estimators. Unit of observation: participant.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Dependent variable: "Cash:" Cash hold at the end of the period 15th (equivalent to the earnings from the asset market).

Independent variables: "# Risky Choices:" Number of times a participant chose the lottery over the certain amount in the Holt-Laury task; "OCrel:" Relative over-confidence measure; 'risk3:" Self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; 'risk5:" Self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)) ; "Age:" Self-reported age of the participant; 'Gender:" Dummy for gender, taking the value 1 if the participant reported to be female.

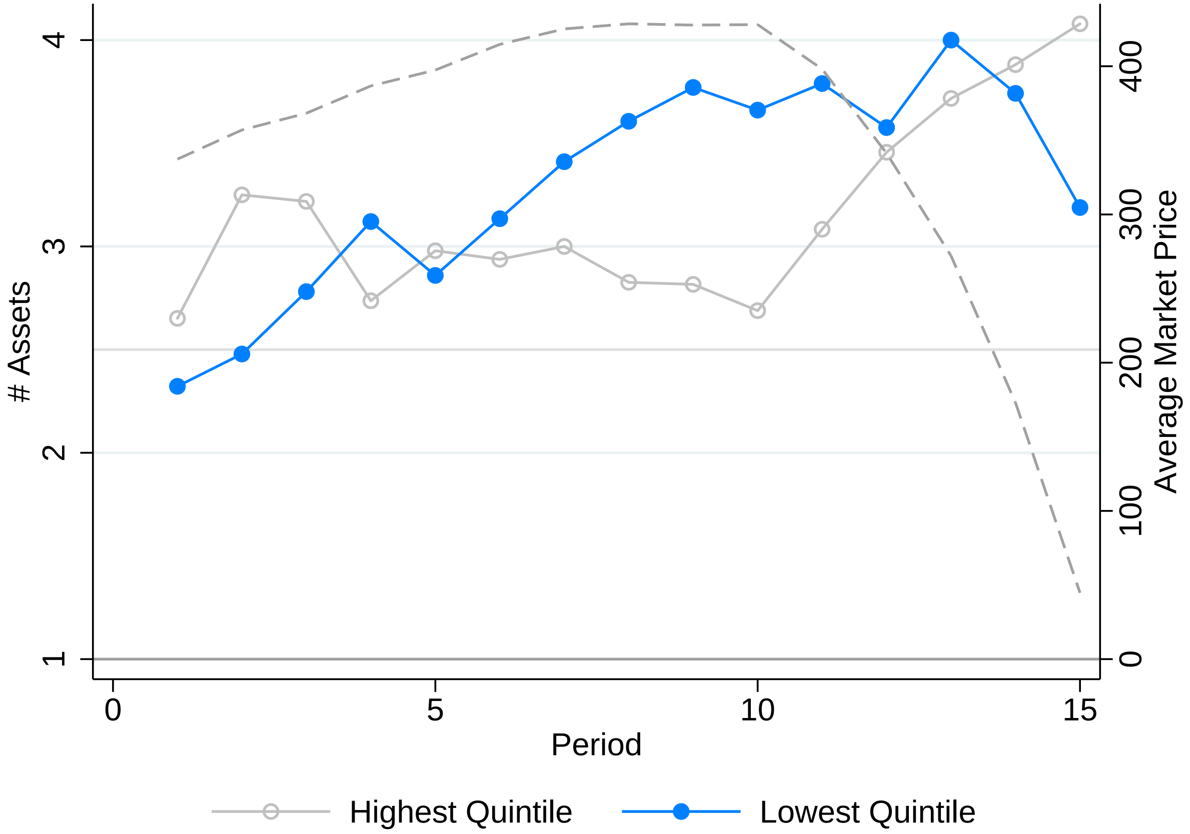
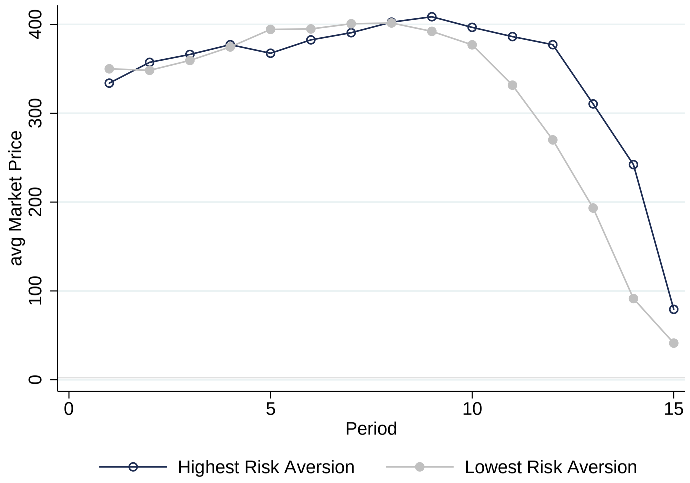


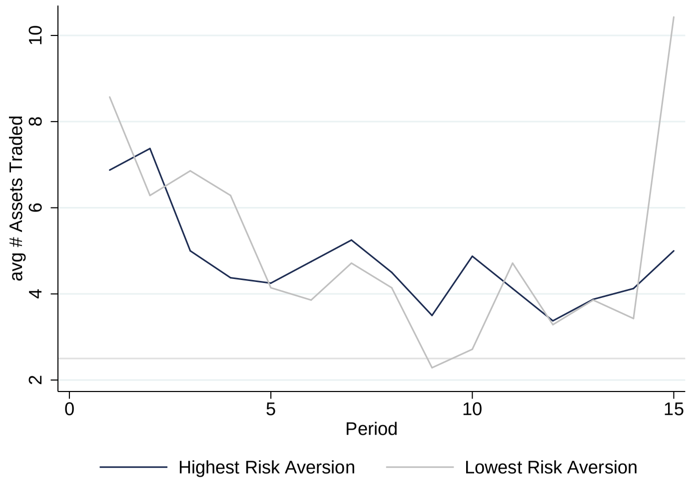
Figure C.3: Mean asset holdings (OCrel)

This graph plots the average market price (dashed line), mean asset holdings for the highest and lowest quintile in the relative over-confidence measures. The highest (lowest) quintile is the group of the 20% of participants who showed the most (least) relative over-confidence according to the measure OCrel and thus can be interpreted as the most (least) relative over-confident group. Participants could either hold cash or assets in their portfolio, thus asset holdings are one outcome of a chosen trading strategy.

C.3 Market outcomes



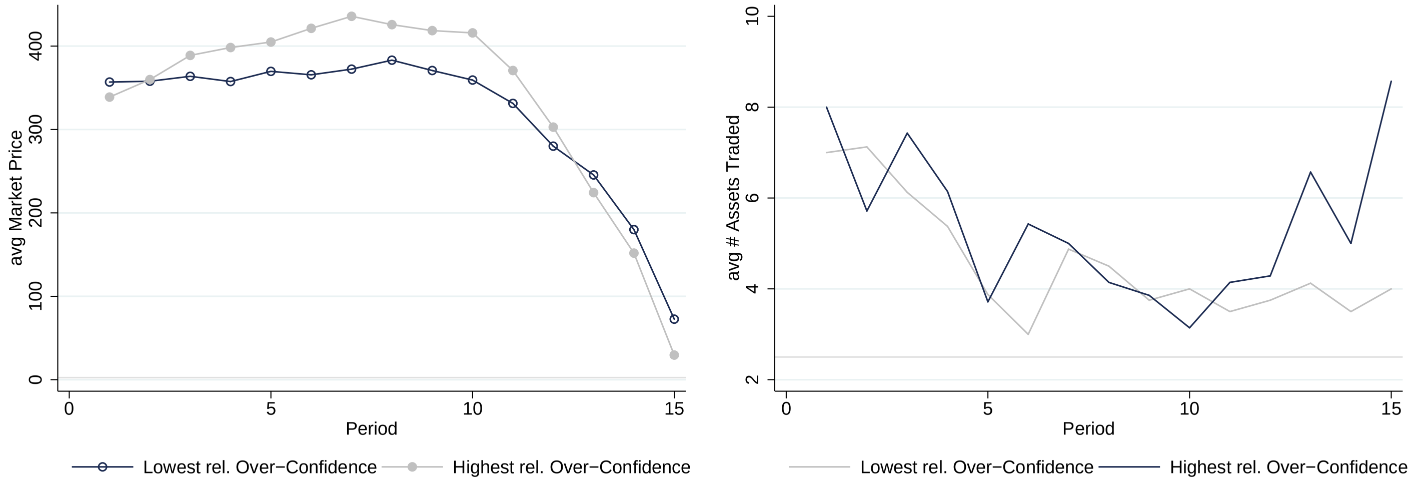
(a) Prices



(b) Volume

Figure C.4: Markets with Highest (Lowest) Risk-Aversion

Each graph compares the markets belonging to the 8 markets with the highest [blue line] (lowest [grey line]) average risk-aversion. Graph (a) shows the average market price over time in each group of markets, where as graph (b) shows the average number of asset traded over time.



(a) Prices (b) Volume

Figure C.5: Markets with Highest (Lowest) relative Over-confidence
Each graph compares the markets belonging to the 8 markets with the highest [blue line] (lowest [grey line])average relative over-confidence. Graphs (a) shows the average market price over time in each group of markets, where as graphs (b) shows the average number of asset traded over time.

Table C.38: Regression on market price, # risky choices

	(1)	(2)	(3)	(4)	(5)
(mean) # Risky Choices	-8.13	-0.44	-23.01*	4.58	-12.01*
	[-18.26,2.00]	[-6.37,5.50]	[-46.07,0.05]	[-3.47,12.62]	[-24.36,0.34]
Constant	426.43***	383.88***	468.16***	286.84***	190.56**
	[306.66,546.20]	[313.76,454.00]	[195.14,741.18]	[191.71,381.96]	[44.08,337.05]
adj. R-squared	7199.41	4175.13	2013.58	374.60	396.09
N	576	379	157	40	39

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: “Market Price:” Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variable: “(mean) # Risky Choices:” Market average number of times participants chose the lottery over the certain amount in the Holt-Laury task

Table C.39: Regression on market price, risk3

	(1)	(2)	(3)	(4)	(5)
(mean) risk3	-20.67*	-15.25**	-45.50*	10.72	-3.51
	[-43.19,1.85]	[-28.98,-1.53]	[-92.25,1.25]	[-6.97,28.41]	[-31.44,24.41]
Constant	390.59***	423.12***	327.60***	309.73***	58.80
	[324.49,456.69]	[382.73,463.51]	[191.14,464.06]	[257.87,361.59]	[-23.36,140.96]
adj. R-squared	7198.65	4170.38	2013.77	374.42	399.91
N	576	379	157	40	39

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean) risk3:" Market mean of self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)).

Table C.40: Regression on market price, risk5

	(1)	(2)	(3)	(4)	(5)
(mean) risk5	-15.91*	-9.10	-27.68	4.34	-0.66
	[-33.28,1.47]	[-20.15,1.94]	[-69.26,13.90]	[-9.79,18.47]	[-22.61,21.29]
Constant	408.02***	429.27***	331.97***	319.66***	51.82
	[322.87,493.18]	[375.23,483.31]	[127.49,536.46]	[250.45,388.86]	[-55.92,159.57]
adj. R-squared	7198.67	4249.17	2015.73	375.57	399.98
N	576	379	157	40	39

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean) risk5:" Market mean of self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)).

Table C.41: Regression on trading volume, risky choices

	(1)	(2)	(3)	(4)	(5)
(mean)# Risky Choices	0.04	0.06	0.08	0.22	1.43*
	[-0.21,0.30]	[-0.23,0.34]	[-0.49,0.65]	[-0.70,1.15]	[-0.00,2.86]
Constant	4.61***	4.78***	3.52	5.67	-10.68
	[1.63,7.59]	[1.40,8.15]	[-3.25,10.28]	[-5.26,16.59]	[-27.63,6.27]
adj. R-squared	3097.51	1946.63	936.73	201.48	236.61
N	600	390	170	40	40

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean)# Risky Choices:" Market mean number of times participants chose the lottery over the certain amount in the Holt-Laury task.

Table C.42: Regression on trading volume, risk3

	(1)	(2)	(3)	(4)	(5)
(mean) risk3	0.19	0.18	0.35	0.13	-1.03
	[-0.36,0.75]	[-0.47,0.84]	[-0.81,1.50]	[-1.91,2.18]	[-4.33,2.28]
Constant	4.58***	4.93***	3.47**	7.91**	9.14*
	[2.95,6.21]	[3.01,6.86]	[0.10,6.84]	[1.93,13.90]	[-0.55,18.84]
adj. R-squared	3097.16	1946.49	936.45	201.71	240.28
N	600	390	170	40	40

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean) risk3:" Market mean of self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)).

Table C.43: Regression on trading volume, risk5

	(1) (mean) TradingVol	(2) (mean) TradingVol	(3) (mean) TradingVol	(4) (mean) TradingVol	(5) (mean) TradingVol
(mean) risk5	-0.07	-0.19	0.31	-0.75	-0.74
	[-0.51,0.37]	[-0.65,0.27]	[-0.72,1.33]	[-2.34,0.84]	[-3.35,1.86]
Constant	5.47***	6.31***	2.97	11.93***	9.78
	[3.33,7.61]	[4.05,8.56]	[-2.07,8.01]	[4.15,19.72]	[-2.98,22.55]
adj. R-squared	3097.53	2135.40	936.46	200.79	240.34
N	600	430	170	40	40

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: “Market Price:” Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: “(mean) risk5:” Market mean of self-reported answer on the question: "How would you asses your willingness to take risks in your professional career?" (0 (try to avoid risks)-10(fully prepared to take risks)).

Table C.44: Regression on Bubble measures, all risk measures

	(1)	(2)	(3)	(4)	(5)	(6)
(mean) # Risky Choices	-0.11			-14.25		
	[-0.69,0.47]			[-43.99,15.49]		
(mean) risk3		0.41			-22.37	
		[-0.86,1.69]			[-88.30,43.56]	
(mean) risk5			-0.15			-23.14
			[-1.16,0.86]			[-74.82,28.54]
Constant	12.06***	9.55***	11.48***	442.66**	339.58***	387.33***
	[5.19,18.93]	[5.81,13.29]	[6.54,16.42]	[91.04,794.29]	[146.29,532.87]	[134.22,640.43]
adj. R-squared	164.35	164.05	164.41	479.19	479.67	479.31
N	40	40	40	40	40	40

OLS regressions, 95% confidence intervals in parentheses. Columns (1)-(3) peak period; (4)-(6) bubble max. Unit of observation: markets.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Dependent variable: Columns (1) - (3) "Peak Period:" Period with the largest deviation of the market price and the expected value; Columns (4)-(6) "Bubble Max:" Largest deviation of the market price and the expected value; "Bubble Component:" Deviation of the market price and the expected value.
Independent variables: "(mean)# Risky Choices:" Market mean number of times participants chose the lottery over the certain amount in the Holt-Laury task; "(mean) risk3:" Market mean of self-reported answer on the question: "How would you asses your willingness to take risks in financial matters?" (0 (try to avoid risks)-10(fully prepared to take risks)).

Table C.45: Regression on market price, OCrel

	(1)	(2)	(3)	(4)	(5)
(mean) OCrel	29.19**	28.91***	38.69	-20.11**	-21.25
	[5.19,53.19]	[15.12,42.70]	[-16.40,93.79]	[-38.49,-1.72]	[-50.44,7.95]
Constant	304.25***	352.72***	161.25***	358.90***	67.83***
	[280.26,328.24]	[338.99,366.45]	[105.64,216.85]	[340.57,377.23]	[38.57,97.09]
adj. R-squared	7196.20	4158.44	2015.53	371.12	397.76
N	576	379	157	40	39

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean) OCrel:" mean of relative over-confidence measure in the market.

Table C.46: Regression on trading volume, OCrel

	(1)	(2)	(3)	(4)	(5)
(mean) OCrel	0.59*	0.35	1.44**	0.85	3.18*
	[-0.01,1.19]	[-0.33,1.03]	[0.10,2.78]	[-1.34,3.05]	[-0.27,6.63]
Constant	4.61***	5.15***	3.15***	7.53***	3.31*
	[4.01,5.21]	[4.47,5.82]	[1.80,4.51]	[5.34,9.72]	[-0.13,6.74]
adj. R-squared	3093.92	1945.78	932.34	201.08	237.18
N	600	390	170	40	40

OLS regressions, 95% confidence intervals in parentheses. (1) all periods, (2) periods before bubble peak, (3) periods after bubble peak, (4) 1st period and (5) 15th period. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Market Price:" Assets hold at the end of the period less the assets hold at the beginning of the period.
Independent variables: "(mean) OCrel:" mean of relative over-confidence measure in the market.

Table C.47: Regression on Bubble measures, OCrel

	(1) (mean) Peak Period	(2) (mean) Bubble Max
(mean) OCrel	-0.32	36.56
	[-1.70,1.07]	[-34.29,107.41]
Constant	11.04***	241.84***
	[9.66,12.42]	[171.21,312.46]
adj. R-squared	164.28	479.03
N	40	40

OLS regressions, 95% confidence intervals in parentheses. Unit of observation: markets.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.
Dependent variable: "Peak Period:" Period with the largest deviation of the market price and the expected value; "Bubble Max:" Largest deviation of the market price and the expected value.
Independent variables:"(mean) OCrel:" mean of relative over-confidence measure in the market.

Part IV

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Part V

Curriculum Vitae

Curriculum Vitae

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